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Water-Energy-Food Linkages in Shared Smallholder Irrigation Schemes

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WATER-ENERGY-FOOD LINKAGES IN SHARED SMALLHOLDER IRRIGATION SCHEMES

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Irrigation is a policy focus in Sub-Saharan Africa and is viewed as an important mechanism to improve farmers' income and livelihoods while reducing the impacts of climate change. Water, energy, and food are linked in intricate ways in irrigated agriculture, and understanding the interplay of these components is crucial for sustainable and profitable crop production. Although studies have been conducted in different parts of the world to understand water and energy use at a field scale under large irrigation systems, little is known about linkages under farmer-managed mechanized irrigated schemes in Sub-Saharan Africa. This study evaluates water-energy-food linkages, engineering and economic performance, current irrigation decision making, and challenges faced around water management in a community-based mechanized irrigation scheme. The research synthesizes intraseasonal water and energy use data for selected crops in a shared center-pivot irrigation scheme in Rwanda. The major cultivated crops are maize and beans (French beans, dry beans, common beans). A daily soil-water balance is central to estimate actual irrigation water requirement (IWR) and is simulated in FAO-CROPWAT 8.0. The study further investigates the variation in water requirements, and the relationship and impacts of this variability on crop yield. Assessment of irrigation performance is done by estimating and comparing crop water productivity (CWP) and crop water use efficiency with global and local averages. Observed irrigation decision-making analyses demonstrate a lack of irrigation planning during growth stages and significant field-to-field variation in irrigation; this is linked to yield reduction in major crops. An econometric model assessment is used to understand the relationship between yield and energy inputs. The energy use assessment includes both direct (electricity) and indirect energy inputs (fertilizers, pesticides, machinery, labor, etc.). This study has implications for understanding irrigation policies in the context of the water-energy-food nexus and decision-making in Sub-Saharan Africa.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1.0 Introduction and Motivation

In Sub-Saharan Africa, nearly 50% of the population lives in poverty (Chen and Ravallion, 2010). The majority of people in rural Sub-Saharan Africa rely on agriculture for their livelihoods. Governments across Sub-Saharan Africa are promoting irrigation development to increase agricultural productivity, food security, and to reduce climate change impacts more broadly. Still, they are struggling to develop systems that are economically sustainable and scalable.

Smallholder farmers (2 ha or less) follow subsistence farming methods. Of all farms in Sub-Saharan Africa, 80% are smallholder farms, averaging 1.6 ha, and producing up to 90% of the total production in the region (Wiggins, 2009). Across the region, irrigation infrastructure is generally not well developed, and most agriculture still depends on rainfall (Dushimumure-myi, 2009). Nevertheless, a broad range of irrigation technologies and activities involves smallholder farmers. “Smallholder irrigation” includes all irrigation activities carried out by smallholder farmers. This includes farmers who manage individual plots or are part of a community-managed irrigation scheme (Nakawuka et al., 2017), using technologies ranging from traditional irrigation technologies such as furrow irrigation to solar-powered pumps. Smallholder farmers in Sub-Saharan Africa receive water for irrigation from shallow wells, streams, rivers, lakes, and ponds using manual or motorized lifting technologies. Conveyance is mostly through open channels, flexible overland pipes, and buckets (Nakawuka et al., 2017).

Compared to Asia, where 37% of cultivated land is irrigated, and globally where 18% of cultivated land is irrigated, official records for Sub-Saharan Africa statistics suggest that of just 6% of cultivated land irrigated (You et al., 2011). Burney et al. (2013) estimated that 40 million ha were suitable for irrigation, while only 7.3 million ha were irrigated. Xie et al. (2014) estimated irrigation expansion potential for four smallholder irrigation technologies (motor pumps, treadle pumps, communal river diversion, and small reservoirs) and found a considerably larger expansion potential of 96 million ha. Therefore, considerable expansion of irrigation appears possible in Sub-Saharan Africa.

Many different forms of irrigation exist in Sub-Saharan Africa. Farmer-led and canal-based irrigation is a common modality (Woodhouse et al., 2016; Harrison, 2018). "Farmer-led irrigation" is any system that has been started by farmers, mainly on their own initiative (Wiggins and Lankford, 2019). In recent years, the scope of what is considered farmer-led irrigation has been changing. In particular, mechanized irrigation schemes are becoming a popular model for irrigation development in Sub-Saharan Africa (Harrison, 2018). One reason for this is the observed recent failures of many large canal-based irrigation schemes that relied on furrow irrigation (Lefore et al., 2019; Harrison, 2018; Mutambara et al., 2016). Another reason is the increasing availability of cheap gasoline and diesel irrigation pumps, and in the last few years, the introduction of solar irrigation pumps.

The success of irrigation schemes varies across Sub-Saharan African countries. For example, research from six irrigation schemes in Mozambique, Tanzania, and Zimbabwe concluded that farmers' lack of skills and poor market access were significant barriers to the success of donor-funded smallholder irrigation schemes (Pittock et al., 2017). A similar study on South African irrigation schemes concluded that 32% of irrigation schemes had failed. However, the overall success rate has roughly doubled since the 1960s, and around 90% of schemes in South Africa introduced between 2000-2009 are still working well. The same study found that community-run schemes, or those run in partnership with governments, performed significantly better than purely government-administered schemes (Mutiro and Lautze, 2015). However, in Tanzania, Nakawuka (2017) reported that even with the improvements of some of the traditional schemes' infrastructures by the government, the performance was low due to poor design, poor management, and poor maintenance. Though many existing smallholder schemes perform at low levels, governments and external donors in Sub-Saharan Africa have planned a substantial expansion of irrigated agriculture (Sullivan and Pittock, 2014).

While studies that relate the success or failure of irrigation schemes in qualitative terms are available in Sub-Saharan Africa, there is a paucity of quantitative data for African irrigation schemes. For instance, water use at an individual farm level is almost never measured in any irrigation scheme (Mwamakamba et al., 2017). In particular, it is unusual to collect data on water and energy use, as well as the costs of these inputs. Understanding the interplay of such factors and how they relate to agricultural productivity and farm-level profitability is critical to understanding the sustainability of any irrigation scheme.

This study focuses on government-funded irrigation schemes for smallholder farmers, which account for 47% of all irrigated land in Africa (Makombe et al., 2001). I seek to estimate water, energy, and food linkages in a mechanized irrigation system to understand the performance of the scheme, its impacts on crop productivity, and the extent to which it is sustainable. The nexus approach is helpful in the systemization of planning and decision making to support sustainable adaptation by acknowledging trade-offs and enhancing policy coherence across the three sectors. Specifically, this study contributes water and energy audit data from a community-based mechanized irrigation scheme and engineering-economic lessons learned from a case study in Rwanda. These kinds of data and lessons are critical to addressing the sustainability and scalability potential of irrigation schemes in Sub-Saharan Africa. Rwanda was chosen for this study because the Rwandan government is prioritizing irrigation development – so much that it seeks to double irrigated area from 2018 to 2024 to over 100,000 ha (MINAGRI, 2017).

To address the performance of mechanized irrigation schemes, performance indicators relating to crop water use, energy use and agronomic functions were identified and estimated. Lifting water for irrigated agriculture is a particularly energy-intensive process in pressurized irrigation. At the same time, agricultural field-operations and inputs (such as seed, machinery, fertilizer, and agrochemicals) result in large energy use in agriculture. Yet, there is minimal information to quantify the use of energy in irrigated agriculture schemes.

Therefore, an energy assessment for selected crops has been presented in the study.

Water and energy are explicitly linked in irrigation and are central to assess the performance of any irrigation project. Additionally, all food production operations require water and energy in different forms. The increase in food supply measures the success or failure of irrigation schemes. De Fraiture and Wichelns (2010) estimated that irrigated schemes could provide 75% of the additional food supply needed by the year 2050 under the condition that crop productivity is improved. Failure to consider water, energy, and food linkages appropriately in resource assessments and policy-making has led to contradictory strategies and inefficient use of resources (Rasul and Sharma, 2015; Howells et al., 2013). The inextricable linkages between water, energy, and food require a suitably integrated approach to analyzing irrigated agricultural production (Figure 1) and its sustainability.

The goal of this study is to assess the performance of smallholder shared mechanized irrigation schemes and to analyze irrigation decision making in a way that can inform future policy decisions. The main objective of the study is to synthesize data that allows food, energy, and water components of agricultural production to be linked at a field scale and intra-seasonally and compared to management practices, agronomic, and economic outcomes. The overarching motivation is that understanding water-energy-food connections will help to improve irrigation decision-making and crop productivity under a community-managed mechanized irrigation scheme. I further show how understanding the relationships between crop yield and energy (direct and indirect) can help in managing or optimizing energy resources sustainably and efficiently.

In later sections, I discuss the methods used to analyze the water-energy-food nexus and to assess the performance of the case study irrigation scheme. This is followed by a discussion describing the study area and data collected. After results, statistical analysis, discussion of policy implications, and conclusions follow.

2.0 Methods

This section discusses the steps used to estimate crop water requirement (CWR) and predict optimal irrigation decision making. The methods section is divided into two subsections: Engineering analyses and Economic analyses. Section 2.2 describes the application of an econometric model to food-energy nexus data in order to analyze energy use and system performance.

2.1 Engineering analyses

In Section 2.1.1, the CROPWAT simulation model used in this study is introduced. The section further demonstrates approaches used to evaluate the implications of irrigation policies in the context of the water-energy-food nexus. Sections 2.1.2 and 2.1.3 detail modeling irrigation requirements, rainfall, and daily soil water balance. Section 2.1.4 describes how estimations from the simulation model are applied to calculate relevant performance indices (the water-food nexus) and Section 2.2.5 details performance assessment of the energy-food nexus.

2.1.1 Modeling Crop water requirements

There are several ways to determine crop water requirements under different environmental conditions; these methods are often guided by the calculation of reference evapotranspiration (ET_0). Modeling ET_0 and actual crop evapotranspiration (ET_c) or crop water requirement (CWR) has been employed for planning irrigation (Moseki, 2019; Stanclaie et al., 2010; Marica, 2005). Several computer models have been developed to simulate crop growth and soil water balance. Among them, the CROPWAT model (Clarke et al., 1998; Smith, 1993) was explicitly designed to estimate CWR, net irrigation water requirements (IWR), to develop irrigation schedules, and to assess reductions in crop yield due to water stress. In this study, CROPWAT 8.0 was used to estimate the various outputs. Seasonal effective rainfall and ET_0 were simulated for each field as the cumulative value for multiple planting dates.

Considering the lack of climatic data for assessing crop water requirements in developing countries, the CROPWAT model can do much to improve irrigation planning and scheduling. All calculations in CROPWAT are based on the widely used and documented FAO-56 (Allen et al., 1998) and FAO-33 methodologies (Doorenbos and Kassam, 1979). Therefore, a brief description of key equations and assumptions is provided here (see Appendix Section A.1 for a complete description of the model). Due to the lack of weather parameters, ET_0 was also estimated using the Hargreaves-Samani (HS) method (Hargreaves and Samani, 1985) to compare with the model simulated ET_0. A detailed methodology used to calculate HS-ET_0 is given in Appendix Section A.1.

2.1.2 Irrigation water requirement (IWR)

A daily water balance approach was deployed in the CROPWAT model to estimate the IWR. The soil-water balance tracks daily changes in soil water storage as a function of inflows from effective rainfall and irrigation and outflows from deep percolation (DP) and ET_c. The daily soil-water balance allows for temporal variability to be observed. On each day, CROPWAT tracks the cumulative depth of soil water depletion in the crop root zone using the soil water balance equation given in equation:

$$D_{ri} = D_{ri-1} - (P_i - RO_i) - I_{ni} - CR_i + ET_{ci} + DP_i \qquad \text{Eq. 1}$$

Where D_{ri} = cumulative root zone depletion at the day's end (mm), i = simulation day, P_i = rainfall (mm), I_{ni} = net irrigation on day i (mm), RO_i = surface runoff (mm), ET_{ci} = Crop evapotranspiration (mm), CR_i = capillary rise from the groundwater table (mm)

Given the high rainfall amounts experienced in the field area (northeast Rwanda) during sowing season A (February-March), the soil-water content is relatively high during the start of crop emergence. So, it was assumed that most farms were starting with a full or nearly full profile. In the CROPWAT water balance calculation, the intake of rain into the soil is determined on a daily basis, and rainfall losses due to DP and RO are estimated based on the actual soil moisture content in the root zone (Smith, 1993). Based on soil and irrigation data provided, a daily soil water balance was developed by the model, which was used to estimate the change in soil water content in the root zone (ΔSW). The

CROPWAT-simulated dataset is provided in Appendix Section A.2. IWR for different crops was simulated in CROPWAT 8.0, using equation 2:

$$IWR = ET_c - P_e \qquad \text{Eq. 2}$$

Gross irrigation (I_g) was measured using water use (measured by water meter devices), which calculate the volume of water applied in the field and time for which the irrigation was applied. Application efficiency was assumed to be 85% to account for losses, including evaporation and wind drift. Net irrigation (I_n) was the assumed depth that infiltrated into the soil and could be effectively utilized by plants. I_n was calculated as application efficiency multiplied by gross irrigation applied. The cumulative IWR for each irrigation event was compared to actual cumulative I_n to understand current irrigation decision-making on a field scale.

2.1.3 Calculation of effective rainfall

Effective rainfall (P_e) is the amount of rainfall infiltrated and stored in the root-zone for plant use. When it is raining, a portion of the rainwater percolates below the root zone of the plants, and a portion flows away over the soil surface as run-off. The plants cannot use these portions of water. The remaining portion is stored in the root zone and can be used by plants. This remaining part is P_e. There are several ways to calculate the P_e based on actual rainfall. For this study, the United States Department of Agriculture Soil Conservation Service (USDA-SCS) method was used in CROPWAT to estimate the effective rainfall. The USDA-SCS method is generally recognized as applicable to areas receiving low-intensity rainfall and to soils that have a high infiltration rate (Dastane, 1978). This method excludes the volume of water lost by runoff and intercepted by crop canopy (Daccache et al., 2014). Effective rainfall (mm per month) gained from the monthly precipitation was estimated using the following equation (Smith, 1993; Dastane, 1978):

i) If $P_{month} \leq 250\ mm,\ P_e = P_{month}(125 - 0.2 * P_{month})/125$ Eq. 3

ii) If $P_{month} > 250\ mm,\ P_e = 125 + 0.1 * P_{month}$ Eq. 4

2.1.4 Performance Indicators for Water-Food Linkages

The performance indicators are intended to characterize the productivity of water use. Crop Water Productivity (CWP) was chosen to understand the water-food nexus, and estimated values were compared with global and local averages. CWP is defined as the physical mass of production or the economic value per unit water (Molden, 1997; Molden & Sakthivadivel, 1999). CWP can be defined in monetary terms ($\$\ m^{-3}$) or production terms ($kg\ m^{-3}$). In this study, CWP is defined as the ratio of marketable yield to crop ET (Foley et al., 2019; El-Marsafawy set al., 2018; Zwart et al., 2004). CWP is a useful tool for looking at the potential change in crop yield that may result from changes in water management.

$$CWP = \frac{Y_a}{ET_c}\ (0.1\text{ha mm m}^{-3}) \qquad \text{Eq. 5}$$

where,

Y_a = marketable yield or actual yield (kg ha^{-1}), ET_c = Crop Evapotranspiration or CWR (mm), 0.1 ha mm m^{-3} = conversion factor, mm to m^3

2.1.5 Energy and Agricultural Linkages

Energy is embodied in all of the inputs and outputs of agriculture. For instance, lifting water for irrigated agricultural production, particularly for pressurized irrigation systems, is an energy-intensive process. However, irrigation scheme planning may fail to take into consideration the present and future energy needs of agriculture. An energy assessment will allow the estimation of the amounts of energy used for agricultural production and can be used to improve the management of energy consumption and to increase energy efficiency.

Based on the types of agricultural inputs, energy input is classified as direct and indirect energy. Direct Energy (DE) use considers energy that is directly embodied in crop production from a power source, e.g. electricity used for pumping irrigation water. Indirect energy (IDE) is dissipated during various farm operations (such as labor, machinery) as well as energy sequestered in seeds, chemical fertilizers, farmyard manure (FYM), irrigation water, insecticides, fungicides, and so on (Chamsing et al., 2006; Singh and Mittal, 1992; Pimentel, 1992). For energy analysis, both direct and indirect energy inputs were included in the calculation as both energy sources incur a considerable cost to agricultural production.

The energy assessment was structured in several steps, as follows:

Step I: Identifying agricultural operations and equipment as energy inputs

In energy analysis, energy and material requirements were estimated for the manufacture and transportation of inputs used for the different agricultural activities that were considered in the study (Kitani et al., 1999). This allowed estimation of the amount of energy used for production and harvest operations in terms of the same functional unit. The input energies (MJ ha^{-1}) used through various input sources, namely seeds, human labor, chemical fertilizers (nitrogen, phosphate, potassium, calcium), machinery (tractor), electricity, and chemicals (insecticides and fungicides) were considered as inputs while marketable yield (kg ha^{-1}) was taken as the output. Indirect energy input data were collected from farmers on a weekly basis, and direct energy use data (electricity) were recorded from a central pumping station for selected center pivot irrigation points, for the time period 2019-2020 (for Season A− Sept-Feb and Season B − Mar-July).

Step II: Estimating energy for physical inputs and operations

The energy equivalent coefficient of an input is defined as the sum of the energy consumed during the production of that input and the energy used for transportation of the input to the end-user or local market (Mousavi-Avval et al., 2018, 2012). One of the methods used to estimate the energy equivalent coefficient is to consider the absolute chemical or physical energy contributed by an input, which is referred to as calorific value. For instance, the calorific value of French beans is 337 kcal per 100g, or a converted value of 14.3 MJ kg^{-1} (USDA, 2019). It is important to note that natural energy sources such as sunlight, rain, wind (which contribute to ET) were not considered in the energy analyses. The energy equivalent coefficients presented in Table 1 were employed in estimating energy use.

Step III. Identifying and estimating performance indicators for the energy assessment

Based on the energy coefficient equivalents of the inputs and output of a crop (Table 1), energy performance indicators were calculated for different crops: energy productivity, specific energy, and energy ratio (Diotto and Irmak, 2015; Romanelli et al., 2012; Zangeneh et al., 2010). Energy productivity (kg MJ^{-1}) can be defined as the ratio of the amount of yield produced, i.e. output to energy use. Specific Energy (MJ kg^{-1}) estimates the amount of energy required to produce a unit crop yield, which is the inverse of energy productivity. The energy ratio measures the energy use efficiency and can be defined as the ratio of total output energy to total input energy.

$$Energy\ Productivity\ (kg\ MJ^{-1}) = \frac{Y_a}{E_i} \qquad \text{Eq. 6}$$

$$Specific\ Energy\ (MJ\ kg^{-1}) = \frac{E_i}{Y_a} \qquad \text{Eq. 7}$$

$$Energy\ Ratio = \frac{E_o}{E_i} \qquad \text{Eq. 8}$$

Where, Y_a = Marketable yield or actual yield (kg ha^{-1}), E_i = Energy input (MJ ha^{-1}), E_o = Energy output (MJ ha^{-1})

2.2 Economic analyses

2.2.1 Econometric assessment of energy use

Econometric analysis can help to explain the food and energy trade-off by quantifying the amount of energy each input contributes towards the total yield. This analysis provides insight into the efficiency of energy use and understanding of the sustainability and profitability of crop production in terms of input energy cost. The starting point of establishing an econometric relationship between energy input and crop yield is to assume a functional form for that relationship. Studies on production functions show the effects of the choice of functional form in determining technology parameters and their economic implications (Zhang et al., 2020; Taheri et al., 2017; Malacarne et al., 2017).

In this study, the many-input or modified Cobb-Douglas production function was used in econometric analyses of the field-level data (Nicholson and Snyder, 2012). A detailed methodology for the model development is provided in Appendix Section A.1. The Cobb-Douglas production function parameterizes the technological relationship between the amounts of multiple inputs and the amount of output that can be produced by those inputs as linear in logarithms. Cobb-Douglas functions have been employed in agricultural and energy applications in a variety of studies by authors investigating the relationship between input energies and yield (Mousavi-Avval and Keyhani, 2012; Singh et al., 2003; Hatirli et al., 2005).

For this study, a Cobb–Douglas production function was estimated using ordinary least square (OLS) estimation. The econometric model assessment was performed using the R-studio program. The Cobb-Douglas production process can be represented as:

$$\mathrm{Y_i} = X_1^{\alpha_1}\, X_2^{\alpha_2}\, X_3^{\alpha_3}\, X_4^{\alpha_4}\, X_5^{\alpha_5}\, X_6^{\alpha_6}\, X_7^{\alpha_7}\, X_8^{\alpha_8} \qquad \text{Eq. 9}$$

where, Y_i = Yield of ith output, α = coefficients of inputs estimated by the model, X_1 = energy input from seed (MJ ha^{-1}), X_2 = energy input from irrigation water (MJ ha^{-1}), X_3 = energy input from fertilizer (MJ ha^{-1}), X_4 = energy input from electricity (MJ ha^{-1}), X_5 = energy input from labor (MJ ha^{-1}), X_6 = energy input from tractor (MJ ha^{-1}), X_7 = energy input from insecticide (MJ ha^{-1}), X_8 = energy input from fungicide (MJ ha^{-1}).

In Eq. 9, the output is expressed as a non-linear function of inputs. The function can be linearized for estimation with OLS by taking the natural logarithm of both sides:

$$\mathrm{lnY_i} = \alpha_1 ln\mathrm{X}_1 + \alpha_2 lnX_2 + \alpha_3 lnX_3 + \alpha_4 lnX_4 + \alpha_5 lnX_5 + \alpha_6 lnX_6 + \alpha_7 lnX_7 + \alpha_8 lnX_8 + e_i \qquad \text{Eq. 10}$$

where, e_i = an error term

The irrigation data used in the econometric analysis were real-time irrigation data observed under the scheme and are independent of the CROPWAT model data. Aggregating direct and indirect energy simplifies the functional relationship to

$$\ln Y_i = \beta_o + \beta_1 ln\mathrm{DE} + \beta_2 ln\mathrm{IDE} + e_i \qquad \text{Eq. 11}$$

where β = coefficients of inputs estimated by the model, DE= total energy input from the direct energy source (MJ ha^{-1}), IDE= total energy input from the indirect energy source (MJ ha^{-1})

One of the features of the log-log functional form of the Cobb-Douglas function is that estimated coefficients represent elasticities. Each coefficient represents the percentage change in the dependent variable (output energies) due to a unit percent change in the explanatory variable (crop yield). In this case, α_i is the elasticity of Y_i with respect to input x_i. When $0 \leq \alpha_i < 1$, that input exhibits diminishing marginal productivity.

Returns to scale (RTS) refers to the rate by which output changes if all inputs are changed by the same factor. Increasing RTS means that when inputs are increased by *x%*, output increases by more than *x%*. Decreasing RTS means that when inputs are increased by *x%*, output increases by less than *x%*. If $\alpha_1+\alpha_2+\ldots+\alpha_n = 1$, the model exhibits constant RTS. If $\alpha_1+\alpha_2+\ldots+\alpha_n > 1$, then the function exhibits increasing RTS, whereas $\alpha_1+\alpha_2+\ldots+\alpha_n < 1$ corresponds to decreasing RTS.

A robust standard error test was performed to check the heteroskedasticity of the model and auto-correlation. A t-ratio or t-statistic was estimated as the coefficient divided by the standard error obtained from the regression analysis. With a large enough sample, t-ratios higher than 1.96 (in absolute value) suggest that the coefficient is statistically significantly different from 0 at the 95% confidence level.

3.0 Study Area and Regional Context

Agriculture plays a vital economic role in Rwanda. It employs about 70% of the population and contributes 29% towards national GDP (World Bank, 2018). Rwanda has a temperate, tropical highland climate, with lower annual average temperatures than typical for equatorial countries due to its high elevation. This makes the region ideal for growing a diverse variety of crops such as maize, wheat, Irish potato, French beans, dry beans, common beans, soybean, sorghum, cassava, sweet potato, banana, groundnut, and other vegetables and fruits (NISR, 2018). The average farm size is 0.6 ha, although 30% of households cultivate less than 0.2 ha, and 15% less than 0.1ha (MINAGRI, 2017).

Precipitation across the region is subject to inter-annual and high seasonal variability (MINAGRI 2011). Therefore, irrigation is an essential component of crop production for small scale farmers. The National Institute of Statistics of Rwanda (NISR) conducted the Seasonal Agricultural Survey (NISR, 2018), indicating that there are 3 agricultural seasons in Rwanda. The climate in Rwanda provides two rainy seasons (Season A and B), with one dry season (Season C) in between. Season "A" extends from November to February of the following year; Season "B", from March to mid-July; and Season "C", from mid-July to September. Major crops in Season A are maize, French beans, and Irish potato. In Season B and Season C, major crops are French beans, dry beans, common beans, tomato, sweet potato, watermelon, Irish potato, and cassava. Most smallholders depend on rainfall alone for farming, and yearly and intraseasonal differences in rainfall – as well as periodic droughts and floods – provide uncertainty for the agricultural community.

3.1 Kagitumba shared mechanized irrigation scheme

Most irrigation schemes in Sub-Saharan Africa are farmer-led surface irrigation systems. Recently, there has been a growing interest in large-scale center-pivot irrigation systems for smallholders by governments as well as multilateral and non-government organizations. Since farmer landholdings are small, center pivots generally must cover multiple farms, which means that irrigation and governance must be shared across multiple farmers. This is a fundamentally different way of irrigating with center pivot irrigation systems than is found in other applications such as in the United States, where one farmer typically operates multiple pivots. A shared irrigation model is used by the Kagitumba Irrigation Scheme. We applied the developed methodology to a case study of the Kagitumba Irrigation scheme in northeast Rwanda in order to understand the impact of mechanized irrigation in smallholder farming and inform current management practices and decision-making. In Kagitumba, the annual rainfall varies from 700-900 mm.

In 2010, the government of Rwanda installed 35 electricity-powered and community-based center pivots in the country in a village named Kagitumba in northeast Rwanda (1.0584° S, 30.4574° E). The government of Rwanda and external donors mobilized substantial resources to finance construction.

Kagitumba is a large irrigation scheme covering 496 farmers on about 460 hectares of land.

Shared or community-based center pivots can be defined as center pivot irrigation operated by or on behalf of a group of farmers for their shared benefit. Each center pivot has a unique set of farm sizes, management practices, and cropping arrangements with varying quality of organization and challenges. As the new community-based irrigation scheme was constructed, the government helped farmers to organize into water users associations (WUAs) to manage their irrigation system and agricultural operations better. Such farmers' organizations have played a prominent role in managing and developing irrigation schemes on a policy level (Harrison, 2018; Venot, 2014). In Rwanda, these kinds of institutions are generally new to the farmers participating, so the government provides organizational standards that include a managerial structure with committees to assist in operation and maintenance, resolve conflicts, collect payments such as water fees, conduct audits, and help with marketing linkages.

Operation and maintenance of the scheme are often the continuing responsibility of the government institution; however, small or low-budget activities (such as changing nozzles, farmers meeting, etc.) are usually carried by the WUA. The Kagitumba WUA collects water fees from farmers, which are used to cover low-budget operations and maintenance items. The water fee is tiered and fixed (i.e. not a volumetric fee) based on crop type and area owned under irrigation per crop season. For instance, the current water fee for French bean is \$53 per ha per crop season. Maize farmers pay a water fee of \$18 per ha per crop season (as of March 2020). Although the maize crop has the highest water requirement under the scheme, French bean farmers pay a higher water fee, reflecting the higher expected profitability of French beans per hectare. French beans are export crops, whereas maize is sold in local markets.

One of the major challenges in the irrigation scheme is siltation and sedimentation due to river water. At Kagitumba, irrigation water is pumped from a centralized pumping station under the scheme, located on Muvumba river. Sediment problems have been observed in other irrigation schemes in other Sub-Saharan African countries withdrawing irrigation water from the Nile basin, which has accounted for scheme underperformance and high operation and maintenance costs (Abera et al., 2018; Al Zayed and Elagib, 2017). Silt and sediment are carried into the irrigation systems, causing increasing silt deposits in irrigation channels and blocking pivot pipes and nozzles. Lack of skills among farmers and lack of agro-processors are amongst the other challenges in Kagitumba Irrigation Scheme.

3.2 Data collection and analysis

The primary data collected in this study were:

- Agronomic data: pivot size, area cultivated, crop type, date of sowing and harvesting, seed, labor, machinery, fertilizers, and agrochemicals applied.
- Weather data: minimum temperature, maximum temperature, and rainfall.
- Irrigation data: irrigation water applied, irrigation time, and energy use.

The methodology for developing this study was structured into several steps, as explained in the previous section. Real-time irrigation water and energy use data were collected based on water meters and energy meter records that were installed in the central pumping station in Kagitumba. To validate the authenticity of data collected and evaluate the irrigation system performance, a catch-can experiment was conducted for selected pivots. The recorded pumping station data were also calibrated and validated by measuring water and energy rates for each pivot at different speed settings, separately. Energy pricing and other cost-based information were provided by farmers and WUA officials. Crops chosen for analysis include maize and beans (French bean, common bean, and dry bean). Of the 35 center pivots in the scheme, 10 center pivots were selected for one-year of water-energy-food nexus analysis. This selection was made based on a variety of factors, such as the functionality of water meters associated with the pivots (almost half of the meters were dysfunctional) and the presence of the major crops selected for this study.

Statistical comparisons were made using ANOVA, graphics, and linear regression to understand variation among water balance components and linkages between crop yield and a water component. Econometric models were constructed using multivariate regression to understand water-energy-food linkages. To check the heteroskedasticity and auto-correlation of the model, robust standard errors for the regression model were calculated, and the t-test of the coefficients was estimated. All the statistical analyses were done using R-program.

4.0 Results and discussion

4.1 Soil properties

Soil properties were obtained from the Rwanda Agricultural Board (RAB) and are presented in Table 2. The research site has a sandy clay loam (SCL) soil type according to soil textures based on the USDA soil triangle (USDA, 1993). The field capacity (FC) and wilting point (WP) of the soil were assumed to be 0.30 and 0.13 m^3m^{-3}, respectively (Schaap et al., 2001). Therefore, the estimated value of available water capacity (AWC) was 0.17 m^3m^{-3} or 170 mm per 1 m of soil. The same soil characteristics were used in CROPWAT 8.0 to simulate daily soil-water balance.

4.2. Evapotranspiration, rainfall and irrigation

Reference ET was calculated using temperature-based methods: the HS-ET_0 method and the CROPWAT-based modified PM method. The HS-ET_0 model tends to overestimate ET_0 (Djaman et al., 2015; Berti et al., 2014) under different climatic conditions; therefore, the CROPWAT 8.0 based modified PM model was used for this study. Statistical analysis performed to compare both the methods resulted in a root mean square error (RMSE) of 0.38 mm/day, and a correlation of 0.70 was found using the Pearson method. A comparison of the ET_0 data, which further indicates no significant difference between the two ET_0 models, is shown in Figure 3 (b). Nonetheless, there is a strong need to develop calibration parameters for both methods for the local climatic condition to precisely calculate the CWR. ET_c was estimated for each field in CROPWAT for selected crops in this study. For Season B (March to mid-July), an average ET_c of 241 mm was found for French bean, 312 mm for both common bean and dry bean. Similarly, for Season A (Sept-Feb), average crop E.T. of 483 mm was found for maize and 229 mm for French beans. French beans are export quality, high value, and shorter duration crops and are grown in all seasons in Rwanda. For 2019-2020, the inter-seasonal comparisons of CWR for the crops included in this study are in the following order:

Maize (483 mm) > Common bean and dry bean (312 mm) > French bean-season B (241 mm) > French bean-season A (229 mm)

Real-time rainfall data (2019-20) were used for this study. Rwanda Meteorological Agency (RMA) did not have available historical rainfall data for its Kagitumba station. However, RMA has historic data for the Nyagatare station, which is 35 km west of the Kagitumba site. Historical data (2010-19) show that the average rainfall for the Nyagatare area is 857 mm. Rainfall data were recorded at Kagitumba using a rain-gauge based weather station. The total annual rainfall recorded for 2018 was 780.9 mm, and in 2019 it was 864.6 mm. In both years, July was the driest month. For estimating crop IWR, effective rainfall was calculated in CROPWAT using the USDA-SCS method (See Appendix A.2). Table 3 presents the mean (± SE) of P_e for French bean, common bean, dry bean (Season B) as 135 ± 4.8 mm, 189 ± 2.5 mm, 202 ± 3.2 mm. Season A crops, maize and French bean had an average P_e of 332.7 ± 2.0 mm and 139.6 ± 67 mm, respectively. The intraseasonal and interseasonal variation in the effective rainfall is due to the different length of crop seasons.

Irrigation Water Requirement was estimated from CROPWAT water balance simulations. The comparisons of inter-seasonal IWR for the crops included in this study are in the following order:

Maize (231 mm) > Common bean (127 mm) > Dry bean (125 mm) > French bean-season B (110 mm) > French bean-season A (98 mm)

As presented in Table 3, mean net irrigation applied (± SE) for French beans, common beans, dry beans (season B) was 104 ± 12 mm, 41 ± 20.8 and mm, and 39.3 ± 9.7 mm and maize (season A) was 61.2 ± 21.5 mm. When compared to IWR, the mean net irrigation applied in most of the crops indicated under-irrigation in the scheme. This suggests that irrigation scheduling with adequate irrigation did not occur during critical growth periods.

The relationships between crop yield and water components (water-food nexus) were established using a linear regression model. Results (Table A.3.1 in Appendix A.3) revealed that applied irrigation had a significant influence on the French bean ($p = 0.030$), maize ($p = 0.09$) and dry bean ($p = 0.028$) yield. However, increasing irrigation applications had a negative impact on the dry bean yield, which cannot be clearly explained from the surveyed data. It is possible that the quality of seed, exact timing rainfall, or other parameters that are omitted from the regression affected the dry bean yield more than applied irrigation. Regression analysis on common bean ($p = 0.11$) showed an overall positive correlation (although not statistically significant) between yield and net irrigation applied. ET_c ($p = 0.0172$) and ΔSW ($p = 0.017$) were found to be significant in influencing maize yield. As shown in Table A.3.1, while most individual effects were non-significant, the collective effect was significant at the 95% and 99% confidence level in maize and French bean.

4.3. Irrigation decision-making

Figure 5 shows the differences between modeled irrigation water requirements and observed cumulative irrigation decision making on a field (i.e. smallholder farm) scale under different pivots and crops over the period 2019-2020. The results show that there was a large gap between observed irrigation and modeled IWR, from which several insights emerge about farmers' field-level irrigation decision-making. On average, net irrigation applied was 95% of the modeled IWR in French Beans. The application depths aligned with the simulated irrigation schedule in different development stages, as shown in Figure 5 (a). This match in the irrigation schedule might reflect that the irrigation in that specific pivot is managed by a co-operative (Farm Fresh) with irrigation managers.

In terms of water-energy-food linkages, as a starting point, one might hypothesize that farmers overapplied irrigation water as they are not required to pay for electricity cost. Recall that there is a fixed water fee charged per season but no variable fee based on the volume of water applied. On the contrary, the results indicate that the farmers seemingly underapplied irrigation as they irrigated only 33% of modeled IWR in common bean, 31% of modeled IWR in dry bean, and only 27% of modeled IWR in maize. One of the reasons for this underapplication could be a lack of irrigation decision-making skills with mechanized systems. Field-to-field variations in terms of applied irrigation were the largest in common beans (51%), followed by maize (35%) and dry beans (25%). French bean farms had relatively low field-to-field variation (11.5%).

An analysis of variance (ANOVA) was carried out to assess the effect of field-to-field variations of water components on the variation in crop yield (Table A.3.2 in Appendix A.3). ANOVA indicated that applied irrigation, ET, and ΔSW (in most of the crops) explained an important portion of the variation in crop yield across the fields. Results also revealed that differences in irrigation had a significant impact on yield variation in French beans and dry beans. Variation in ΔSW had a significant impact on yield in maize.

Results (Figure A.3.3 in Appendix A.3) further indicate that irrigation is critical in the mid and late developmental stages of maize (season A). In contrast, for season B crops, irrigation was found to be crucial in the mid-developmental stage. In field crops, well-planned and scheduled irrigation can increase CWP. However, an inevitable yield reduction should be expected in water stress conditions. Based on ground observations, cumulative irrigation (an average seasonal net irrigation of 40-50 mm) was insufficient to maintain a wet soil profile, resulting in a significant grain yield reduction within the range of 9 to 21% in maize. Interestingly, maize planted in early August had no reduction in yield because of high rates (209 mm) of rainfall in October (aligning with the mid-to-late developmental stages of maize). Hence, the yield loss is mainly associated with intraseasonal irrigation scheduling. These yield reductions were calculated in CROPWAT as a response to water deficits. The CROPWAT model did not predict significant yield reductions in beans (with a range of 0.5% to 9%).

However, even if the water requirements of the entire scheme are met for a system with poor uniformity, significant volumes of water will go directly to return flows. For this reason, an irrigation system evaluation for selected pivots was conducted, and distribution uniformity (DU) and coefficient of uniformity (CU) were tested. Results (Appendix A.1.4) show that both DU and CU were consistently below 80%, suggesting that a poor application uniformity was achieved in those fields, and further improvements are possible. Application uniformities can be improved by using matching nozzles placed according to design specifications appropriately spaced, together with simple maintenance, such as checking operating pressure, ensuring nozzles are fixed well, not clogged, and are correctly rotating.

4.4. Assessment of performance indicators

Performance indicators based on water and energy use were calculated and discussed to assess the performance of crops and the irrigation scheme broadly.

4.4.1 Assessment of water-based performance indicators:

Crop water productivity was calculated to compare the performance of crop response to water required or net water applied on the field scale. The CWP for each crop in both cropping seasons is presented in Table 3. CWP for French bean, common bean, dry bean, and maize lies within the range of 1.6-4.2 kg m^{-3}, 0.2-0.5 kg m^{-3}, 0.2-0.5 kg m^{-3}, and 0.7-1.7 kg m^{-3}, respectively. There is very limited literature on CWP values for beans to be considered as a global or local average range. A distribution plot of the CWP range for each crop is shown in

Figure 4. $CWP_{Dry\ bean}$ reported by FAO-33 ranged within 0.3-0.6 kg m^{-3}. Satriani et al. (2015) reported $CWP_{Dry\ bean}$ within the range of 0.17-0.30 kg m^{-3} in Southern Italy. Nielsen (2018) reported an average $CWP_{Dry\ bean}$ of 0.82 kg m^{-3} in Colorado. Comparing observed $CWP_{Dry\ bean}$ to the previous literature indicated that $CWP_{Dry\ bean}$ falls within the range of FAO-33; however, it still shows scope for improvement.

In French beans, the results showed that CWP progressively increased when water application increased from 90 to 112 mm. Irrespective of the same amount of irrigation water applied, CWP varied broadly from 1.6-4.2 kg m^{-3}, suggesting additional factors beyond applied irrigation are contributing to changes in CWP. As a comparison, Lado et al. (2017) reported $CWP_{French\ bean}$ in Kenya, which varied from 2.23-3.24 kg m^{-3}.

CWP_{Maize} in Tanzania was found to be in the range of 0.40-0.70 kg m^{-3} by Igbadun (2006). Greaves and Wang (2017) reported a CWP_{Maize} within a range of 1.52-2.25 kg m^{-3}. According to Zheng et al. (2018), the global average CWP per unit water depletion was 1.86 kg m^{-3} for maize, with a typical range of 1.1-2.7 kg m^{-3} (Zwart et al., 2004). In a meta-analysis, Foley et al. (2019) categorized CWP_{Maize} as low CWP ($\leq$1.25 kg m^{-3}), medium CWP (>1.25 to $\leq$1.75 kg m^{-3}), and high CWP (>1.75 kg m^{-3}). Bhatti (2017) reported CWP_{Maize} within a range of 2.0-2.3 kg m^{-3}, and Djaman et al. (2018) reported a CWP range of 1.3-1.9 kg m^{-3} in Nebraska. In this study, the mean CWP_{Maize} was less than 1.25 kg m^{-3} indicating a low CWP as compared to global values. Generally, field-to-field variation in CWP among different crops is due to differences in genotypes, agricultural practices, soil pH and organic matter, and disease, amongst other factors (Zheng et al., 2018). Closing the CWP gap is important to ensuring food security and sustainable production, especially in the context of Sub-Saharan Africa, as there is a large potential to increase crop production. In the current situation, there appears to be significant potential to improve the CWP for major crops through proper water management.

4.4.1 Assessment of energy-based performance indicators:

Physical inputs and their embodied energy consumed are presented in Table 1. The weighted mean of farms under different pivots was taken to calculate the quantity of each energy input and their total embodied energy for crop production. For instance, on an average, for the production of 1 ha of French bean, 43 kg seed, 3032 hrs of human labor, 3 hrs of tractor time, 203.21 kg Nitrogen-phosphorus-potash mixture (NPK), 195.60 kg di-ammonium phosphate (DAP), 220.45 kg Calcium Ammonium Nitrate (CAN), 0.87 kg insecticide, 11 kg fungicide, 342 m^3 irrigation water, and 282 kWh were used. The highest input energy was contributed by fertilizer (50%), followed by human labor (25%) and irrigation use (14%). For the production of 1 hectare of common bean, human labor (50%) contributed the highest amount of energy, followed by irrigation (36%). For dry beans, irrigation (43%) contributed the highest amount of energy, followed by human labor (28%). Management practices for common bean and dry bean included no expenditures for fertilizer, agro-chemicals, or machinery. On average, for the production of 1 ha Maize, 25 kg seed, 1032 hrs of human labor, 3 hrs tractor, 203.21 kg Nitrogen-phosphorus-potash mixture (NPK), 195.60 kg di-ammonium phosphate (DAP), 0.87 kg insecticide, 694 m^3 irrigation water, and 400 kWh were used. Irrigation (43%) contributed the highest amount of energy in maize production.

Intraseasonal analysis among different kinds of beans indicated that French bean was the most energy-consuming crop, while also producing the maximum energy output. A comparison between input-output energy ratio, energy productivity, and specific energy is presented in Table 4. The output-input energy ratio is one of the indicators that show the energy use efficiency of crop production. Among the crops, maize had the highest energy ratio and energy productivity. This means that with energy productivity of 0.41 kg MJ^{-1}, maize produced the maximum amount of biomass among the crops for a given amount of input energy. French beans had the highest energy demand among different crops. Maize also had the highest energy ratio of 6.1. This indicates energy use efficiency is highest in maize. One of the reasons energy ratios are higher than 1 is because energy coming from sunlight or other natural resources is not factored into energy analyses.

The water-energy-food curve (Figure A.3.4) for different crops revealed higher energy intensity in French bean than for the other crops. Overall, no correlation between yield and water use was found from the curve. However, energy use showed some level of positive correlation with yield. The graphical analysis showed energy use could be decreased for many smallholder farms without hurting yield.

4.6. Econometric Modeling assessment

In order to understand input energies and yield relationships in more detail, econometric models were constructed and estimated. As can be seen from Table 5, irrigation water, machinery/tractor, and fungicide had a positive impact. The impact of irrigation water, fungicide, and insecticide were found statistically significant on French bean yield at 10% ($p = 0.097$), 1% ($p = 0.006$), and 5% ($p = 0.043$), level, respectively. Irrigation water had the highest impact (elasticity = 0.6), among other inputs. The elasticity interpretation is that a 1% increase in irrigation water input would lead to a 0.6% increase in yield under these circumstances, all else equal. The second valuable input was found as fungicide with an elasticity of 0.3 and a significant contribution to productivity, followed by machinery with 0.2 elasticity. Insecticide input showed a negative coefficient (–0.14). Narrowly interpreted, this would suggest that there could be a decrease in crop yield with a further increase in insecticide input. However, this is not a reasonable explanation from a practical level. Contextually, with an increase in the insect population, insecticide input would also increase to reduce the infestation. But, higher insecticide use indicates a higher insect population and hence more damage to the crop. The relevant counterfactuals, namely yield with infestation but without insecticide, and yield without infestation but with insecticide, are not observed. Overall, it is likely that the negative coefficient on insecticide is a result of omitted variables related to infestation.

Additionally, Equation 11 was employed to model DE and IDE on the French bean yield. The regression results indicated that the DE and IDE were significant at 1% ($p = 0.00033$) and 5% levels ($p = 0.028$), respectively. The RTS values for Equation 10 and Equation 11 were 0.76 and 0.47, respectively, which gives evidence of decreasing returns to scale. In other words, a 1% increase in the total input energy would lead to a < 0.64 % increase in the French bean yield for the model. Note that only coefficients of significant energy inputs were added in calculating returns to scale: adding coefficients that are not significantly different to zero and then interpreting them is not a meaningful exercise.

Econometric model estimates for common beans showed that irrigation water and labor had a positive impact on the common bean yield. Labor was found to be statistically significant ($p = 0.070$). Irrigation water had the highest (0.321) impact, among other input energies. Irrigation water was followed by labor with a 0.28 elasticity, which significantly contributed to productivity. This indicates that a 1% increase in the energy irrigation water input led to a 0.28% increase in yield in these circumstances. The estimations for Equation 11 indicated that the IDE was significant ($p = 0.044$). The RTS values for Equation 10 and Equation 11 were 0.29 and 0.32, respectively, which gave evidence of decreasing RTS.

For dry bean, econometric estimates revealed that labor input had a positive impact on the yield. Labor had the highest elasticity (0.135) among other energy inputs and significantly contributed to the dry bean productivity ($p = 0.040$). Other energy inputs were estimated to be non-significant. Additionally, the estimates from Equation 11 indicated that overall IDE sources did not significantly contribute to crop production, and DE had a negative impact on dry bean production. The RTS values for Equation 10 and Equation 11 were 0.14 and 0.07, respectively, suggesting a decreasing RTS and that adding further IDE input would not increase the crop yield.

Econometric model estimates for maize suggested that irrigation water, fertilizer, and machinery had a significant positive impact on the yield. Irrigation water ($p = 0.078$) had the highest elasticity (0.27), among other energy inputs. The second important input was found to be fertilizer with 0.06 elasticity and a significant ($p = 0.085$) contribution to crop productivity, followed by machinery ($p = 0.094$) with 0.07 elasticity. Additionally, the estimates from Equation 11 indicated that the IDE source had a significant impact ($p = 0.053$) on the maize yield under given circumstances. The RTS values for Equation 10 and Equation 11 were 0.40 and 0.15, respectively, suggesting a decreasing returns to scale relationship between the energy equivalents of inputs and yield. Thus, a further increase in inputs would produce less than a proportionate increase (less than 0.15% for a 1% increase) in output, under these circumstances.

5.0 Policy Implications

The analysis in this study has several important implications for understanding the trade-offs between water and energy resources in mechanized irrigation schemes in Sub-Saharan Africa. For implementing any community irrigation scheme, a socio-economic study of the potential area is essential as the farming community is diverse. Multiple crops can be successful if proper irrigation planning is done before planting. Policies linking incentives to manage irrigation among the community and the government's objective for smallholder irrigation will be helpful to the success of similar irrigation schemes.

The potential range of water requirements for all planted crops must be known at the beginning of each growing season so that a tentative irrigation schedule can be drawn up for proper planning and designing irrigation rates to meet the growth needs of crops. Current irrigation behaviors in the Kagitumba irrigation scheme suggested that under-irrigation is common in all the crops except French bean. Planting dates and crop developmental stages are of immense importance to understand peak requirements for irrigation water. Not considering water requirements during different developmental stages would not only lead to potential water wastage but also may lead to a negative impact on crop yield, as seen in current irrigation behavior at Kagitumba.

Potential exists to improve irrigation water management and crop yield through better irrigation scheduling techniques. There are several ways in which this goal might be achieved. Increasing educational efforts through procding extension-type services is one option. Alternately, it may be possible to incentivize farmers and WUAs to maintain good irrigation scheduling practices (Pittock et al., 2017); in this case they might receive both a monetary incentive for good practices and the increased crop yield resulting. Other possible options include the use of adaptive regulations that are linked to improving behavior in the irrigation decision-making process and technological advances such as variable rate irrigation to manage water optimally to target better crop yield. All of these approaches would require investing in people and institutions as much as in mechanization. The costs of implementing capacity building and farmers' training are often a small fraction of the capital cost of setting up irrigation schemes. One policy option is to factor long-term education and extension costs into the design of projects, rather than to add them when schemes are starting to fail (Pittock et al., 2017).

As currently implemented at Kagitumba, the government does not charge farmers a variable cost for electricity using in irrigation pumping. The per-hectare, per-season fixed water costs payable to the Water Users Association are also modest. If the farmers were to pay actual electricity costs for mechanized irrigation, then coupled with the high labor costs found in the scheme, switching to higher-value crops would be necessary for profitability.

Despite the emphasis on the labor-saving potential of mechanized irrigation over hand-carried hosepipe and sprinkler systems, large amounts of labor are associated with almost all sorts of field operations (land preparation, planting, weeding, fertilizer application, chemical spraying, and harvesting) in Kagitumba. This reflects complementarity rather than substitutability between investments in irrigation technology and labor use. Finally, as observed in the Kagitumba irrigation scheme, system breakdowns occur during the peak irrigation period, which poses high operation and maintenance costs and could be one of the major reasons for reduced crop performance.

6.0. Potential Future Research

In many mechanized irrigation schemes, there is evidence of system breakdowns during the irrigation season. One of the primary reasons for this in Kagitumba is high sedimentation in the Muvumba river (the irrigation water source) from erosion of upstream catchment areas during season A and B. A potential future study would be an assessment of the water quality of irrigation water at the study site. If the water quality is poor, it could lead to severe salinity problems in the soil as well as irrigation system breakdown in the longer term.

For accurately estimating the ET, precisely calibrated Kc values are required in countries across Sub-Saharan Africa; little of these data exist. FAO-56 Kc values may be satisfactory for estimation of CWR on a basin level, but this does not consider large variability in crop phenology arising from a different climate and agronomic practices on a farm scale. Research on developing Kc values for major crops would be a potential contribution to the research community. Further research focusing on comparing the productivity or efficiency under pivot-irrigated crop production to other methods of irrigated and rainfed production would be useful. This would help to understand if there is a need for investment in center pivot irrigation systems or some other community-based irrigation that may be suitable for sustainable smallholder farming.

There is limited work done on water-energy-food simulation models to optimize water and energy resources for better crop yields. An optimization module based on algorithms could be included in the simulation model to analyze an optimal and sustainable solution. Future studies could also extend the analyses to analyze the impacts of changes in the market price of inputs and outputs. Sensitivity and uncertainty analysis could analyze the implications of parameter and model uncertainty on the results. Finally, the econometric results could also be used in a policy analysis to understand the degree to which observed levels of input use are consistent with economic profit maximization.

7.0. Conclusion

Increasing the availability of mechanized irrigation is a stated policy goal across Sub-Saharan Africa and is viewed as a pathway to improve smallholder farmers' incomes and reduce the impacts of climate change. Little is known about water-energy-food linkages under mechanized irrigated schemes in Sub-Saharan Africa. This study evaluated these linkages for a large communal center-pivot irrigation system in Rwanda. Data around engineering and economic performance and current irrigation decision making were collected and analyzed. In particular, the intraseasonal water and energy use to assess the performance of the mechanized irrigation scheme. Among the different crops under the scheme, maize had the highest CWR and IWR, followed by common bean and dry bean. Results suggest that effective planning of irrigation water management (e.g., irrigation scheduling) could improve the yield and performance of the scheme.

Significant field-to-field variation in terms of net irrigation applied was found in French bean and dry bean, while the modeled irrigation rates remained similar across the fields. Surprisingly, the water use mapped to individual fields (smallholder farms) suggested under-irrigation. Current irrigation decision-making in season A and B crops (except French bean) did not match well with modeled irrigation rates. Less irrigation application was observed during the critical growth development stage than modeling would suggest is required, resulting in significant yield reductions. As observed in the Kagitumba irrigation scheme, there are several irrigation system breakdowns during the peak irrigation period, which could also be one of the reasons for reduced irrigation and crop yield. Also, the irrigation systems evaluation revealed that poor application uniformity was achieved in selected pivots, leaving room for further improvements.

The econometric analysis of water-energy-food linkages suggested that irrigation has a positive impact on the yield of crops, and additional irrigation could have produced better results, except for dry beans. We suspect that some other management practice or disease occurrence (as no plant protection is used) impacted the dry bean yield.

In terms of performance indicators, the average CWP_{Maize} was less than the low global CWP benchmark ($\leq$1.25 kg m^{-3}), and the average $CWP_{French\ bean}$ was more than local standards ($\approx$ 2.7 kg m^{-3}). This gives some evidence that the CWP_{Maize} could be further improved to improve food security. Energy-based performance indicators indicated that French bean production used the highest energy input (total energy demand of $\approx$ 24,435 MJ ha^{-1}) among the studied crops. In the mechanized irrigation scheme, human labor remained one of the most crucial energy inputs for dry bean and common bean production, demonstrating that human labor is also an essential factor even after mechanization.

A parametric approach using econometric models was applied to study the energy-food nexus. Regression analyses revealed that the relative importance of inputs on determining output varied by crop type. Irrigation water and fungicide inputs had the highest impacts on French bean output, and the use of labor had a substantial impact on common bean and dry bean yield. In maize, the use of irrigation water, machinery, and fertilizer inputs had strong positive impacts on crop yield. While some crops are being grown profitably, the overall scheme performance was deemed low based on the irrigation system and decision-making analyses, crop water management and planning, and comparing technical performance indicators to global and local averages.

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Tables

Table 1. Input and output energy use equivalents taken from various literature. Electricity used for pumping irrigation water is a direct energy source. The rest of the energy inputs are classified as indirect energy sources.

Energy sources	Units	Energy equivalents (MJ)	References
Human	hrs	1.96	Kitani, 1999
Machinery			
(a) Tractor	hrs	64.8	Kitani, 1999
(b) Farm machinery	hrs	62.7	Kitani, 1999
Electricity	kWh	12	Kitani, 1999, Singh, 2002
Fertilizers			
(a) N	kg	78.1	Kitani, 1999
(b) P2O5	kg	17.4	Kitani, 1999
(c) K20	kg	13.7	Kitani, 1999
(d) FYM	kg	0.3	Singh, 2002
(e) NPK (15:15:15)	kg	16.4	Calculated (Appendix A.1.3)
(f) CAN	kg	21.9	Calculated (Appendix A.1.3)
Herbicides	kg	238	Heidari et al., 2010
Insecticides	kg	199	Kitani, 1999
Fungicides	kg	92	Kitani, 1999
Irrigation water	m^3	0.63	Singh, 2002
Seeds and Output			
French beans	kg	14.3	USDA, 2019
Common beans	kg	14.1	USDA, 2019
Dry beans	kg	20	Ali et al., 2018
Maize	kg	14.7	Singh et al., 1992

Table 2. Soil texture for different sections under the Kagitumba Irrigation Scheme. Soils were classified as Sandy Clay Loam based on the USDA soil triangle.

	Depth	Soil pH	Sand (%)	Silt (%)	Clay (%)	FC (%)	WP (%)
Section A	0-30 cm	5.5	55	18	27	36	16
Section B	0-30 cm	5.0	65	13	22	36	16
Section C	0-30 cm	5.6	65	16	19	36	16

Table 3. Summary table for measurements yield and water components: crop evapotranspiration, net irrigation applied, effective rainfall, change in soil water storage in the root zone, and crop water productivity.

	French Bean	Common Bean	Dry Bean	Maize
Yield (kg ha^{-1})				
Min	4019	577.8	679	3528
Max	10144	1676	1415	8012
Mean ± SD	7092 ± 1664	944.3 ± 244	1033.2 ± 120	5363.4 ± 868
CWP (kg m^{-3})				
Min	1.6	0.2	0.2	0.7
Max	4.2	0.5	0.5	1.7
Mean ± SD	2.9 ± 0.72	0.30 ± 0.07	0.3 ± 0.07	1.11 ± 0.18
ET_c (mm)				
Min	223	306	306	481
Max	249	317	323	491
Mean ± SD	241 ± 8.8	312 ± 2.8	313 ± 3.5	483 ± 2
Ia (mm)				
Min	89.3	23.7	21.8	36.7
Max	126.9	76.1	47.2	93.3
Mean ± SD	104 ± 12	41.0 ± 20.8	39.3 ± 9.7	61.2 ± 21.5
Pe (mm)				
Min	129	184	196	322
Max	145	193	210	341
Mean ± SD	135 ± 4.8	189 ± 2.5	202 ± 3.2	333 ± 2.0
ΔSW (mm)				
Min	8.6	33	72.2	54.8
Max	38.9	79.1	94.2	139.3
Mean ± SD	23.7 ± 8.4	56 ± 13.1	82.6 ± 5.5	129 ± 13.4

Table 4. Estimated energy indicators for different kind of beans and maize

	French Beans	Common Bean	Dry Bean	Maize
Energy Use ‘000 (MJ ha^{-1})	24.4	5.0	6.0	13.4
Energy Ratio	4.2	2.8	3.1	6.1
Specific Energy (MJ kg^{-1})	3.6	5.5	6.0	2.6
Energy Productivity (kg MJ^{-1})	0.3	0.2	0.2	0.4

Table 5. Econometric estimation results. The data in the table represents coefficients or elasticities obtained from econometric estimation and the data within parentheses represent standard errors

	French Bean	**Common bean**	**Dry bean**	**Maize**
	N=24	**N= 40**	**N= 73**	**N= 58**
Seed	0.029	-0.067	-0.079	-0.219
	(0.396)	(0.081)	(0.192)	(0.157)
Irrigation water	0.596*	0.321	-0.058	0.272*
	(0.337)	(0.294)	(0.049)	(0.151)
Fertilizer	-0.079	-	-	0.061*
	(0.177)			(0.035)
Electricity	-0.130	-0.307	-0.06	-0.175
	(0.144)	(0.21)	(0.07)	(0.150)
Labor	-0.138	0.285*	0.135**	0.087
	(0.181)	(0.153)	(0.065)	(0.088)
Tractor	0.201	-	-	0.066*
	(0.622)			(0.038)
Fungicide	0.305***	-	-	
	(0.095)			
Insecticide	-0.143**	-	-	-0.035
	(0.065)			(0.052)
RTS	0.76	0.29	0.14	0.40
Direct energy	0.051***	-0.114	-0.082	0.012
	(0.012)	(0.087)	0.069	(0.048)
Indirect energy	0.42**	0.32**	0.16	0.138*
	0.177	-0.154	0.103	(0.070)
RTS	0.47	0.32	0.074	0.14

*p<0.1; **p<0.05; ***p<0.01
RTS= returns to scale
N= number of observations or farms

Figures

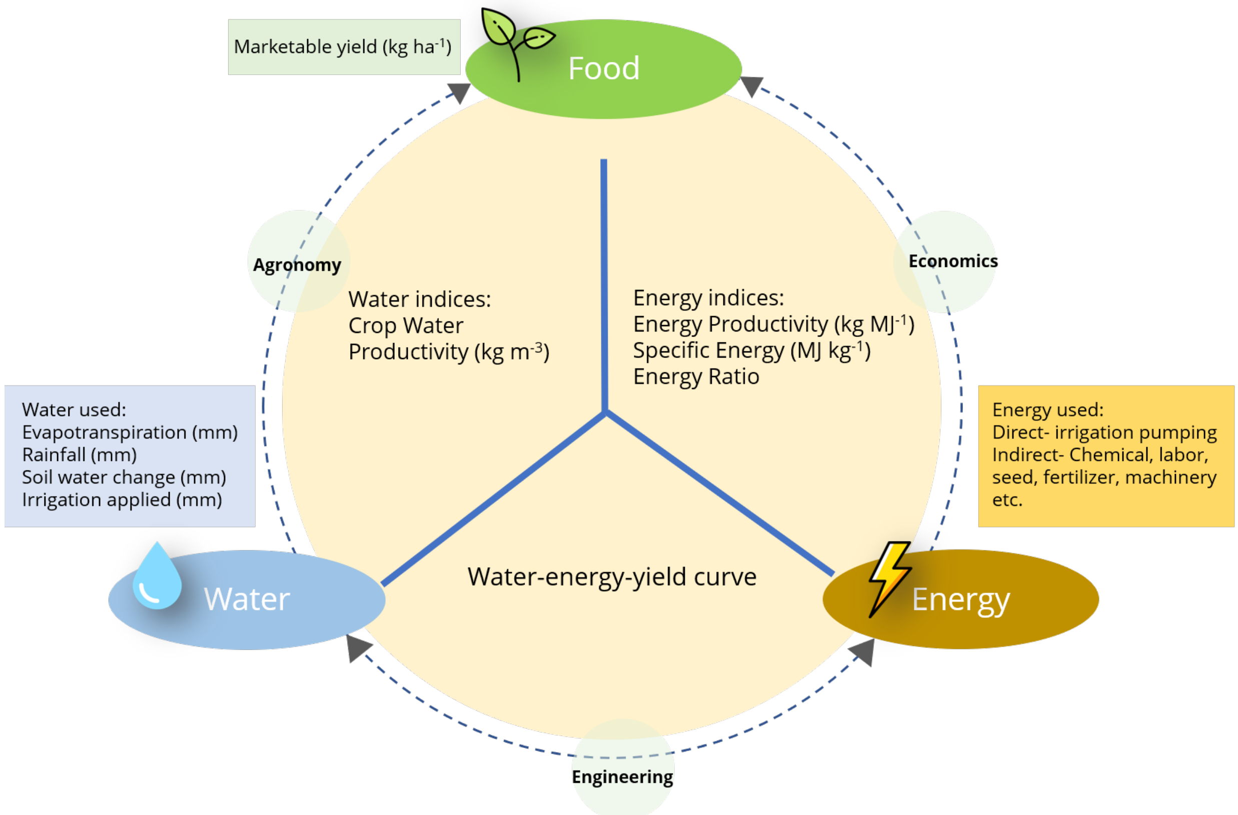


Figure 1. Conceptual diagram of water-energy-food nexus for evaluating irrigation performance

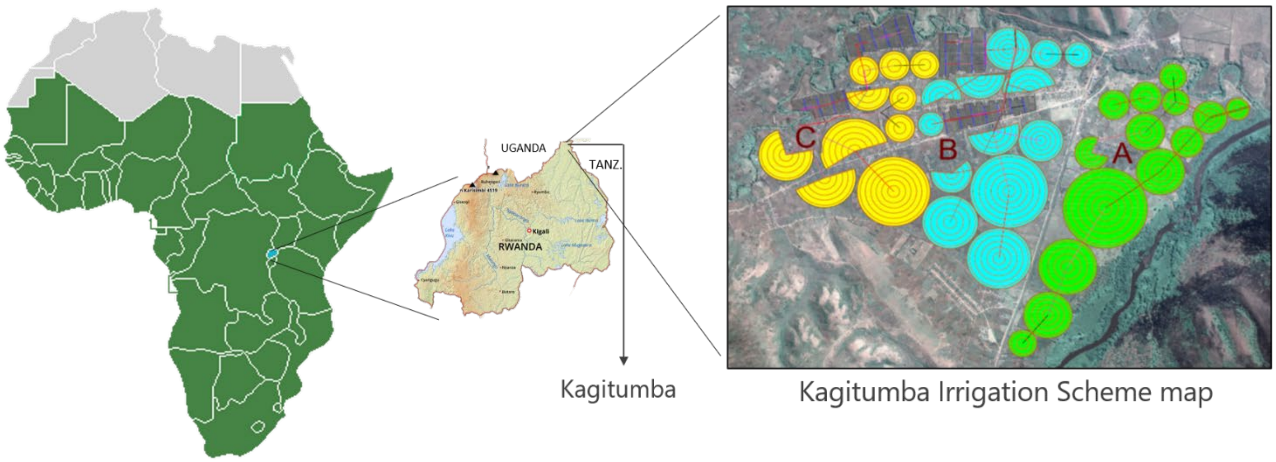


Figure 2. Study site showing the Kagitumba Irrigation Scheme in Rwanda and Sub-Saharan Africa map

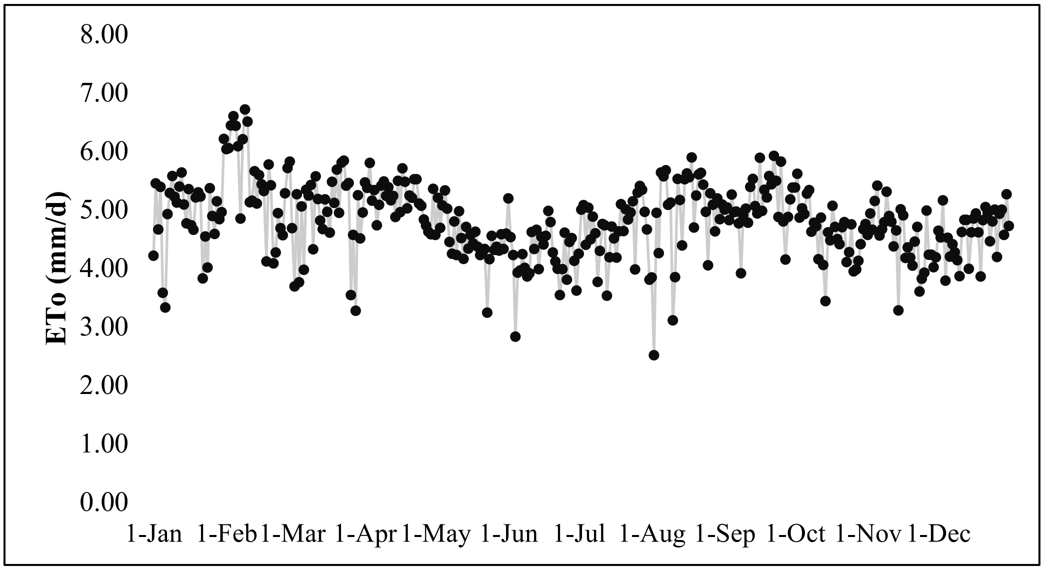


Figure 3(a). Daily reference evapotranspiration (ET0) for the Kagitumba Irrigation Scheme calculated using the HS-ET0 method

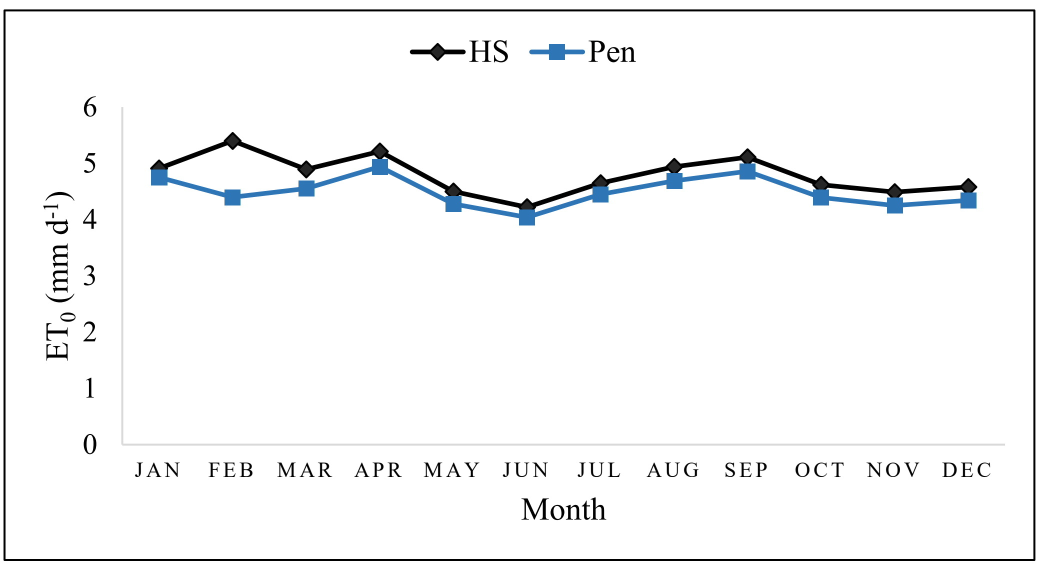
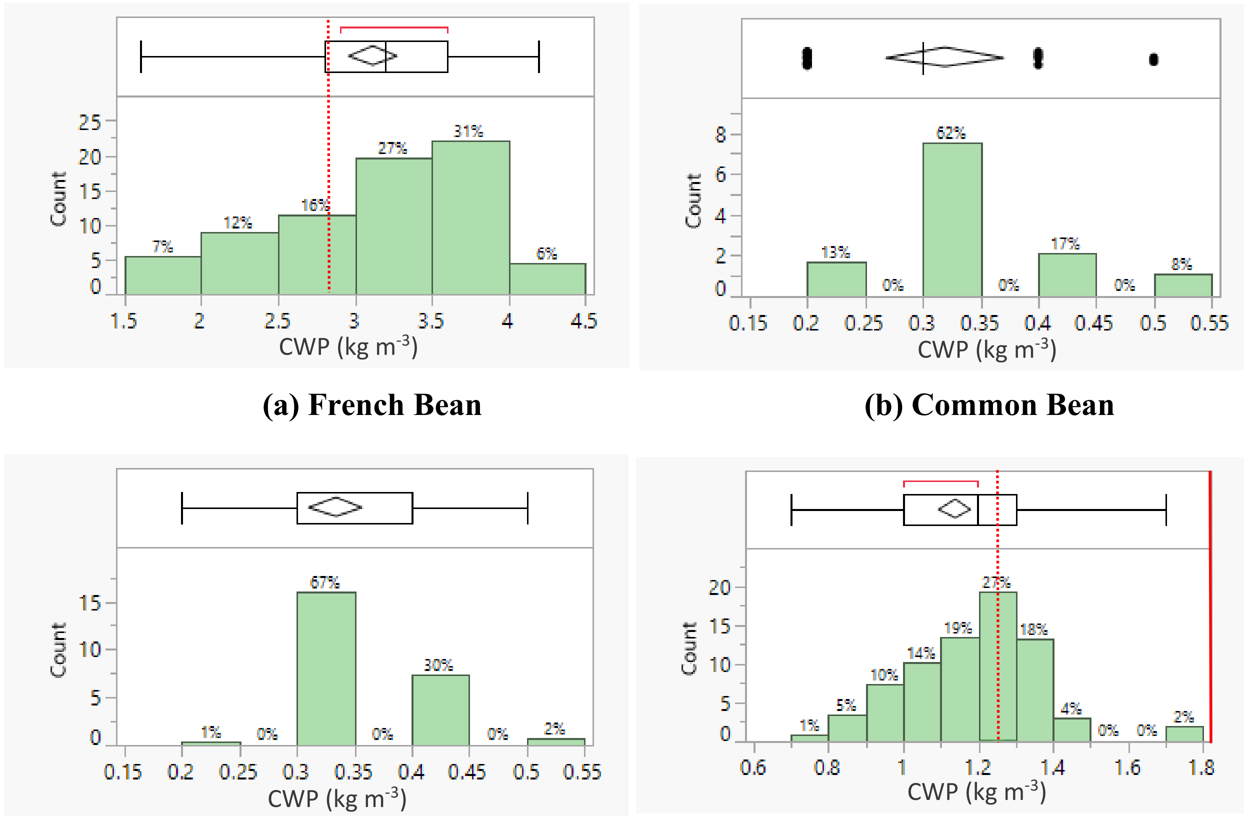


Figure 3(b). Comparison of reference ET estimated by the HS-ET0 method and CROPWAT modified PM method



(a) French Bean **(b) Common Bean**

(c) Dry Bean **(d) Maize**

Figure 4. Distribution of crop water productivity for French Beans, common beans, dry beans and maize. The dotted line on panel (a) shows the local average CWP of French bean. The solid line on panel (d) shows the global average maize CWP and, dotted line shows the benchmark below which CWP is considered low.

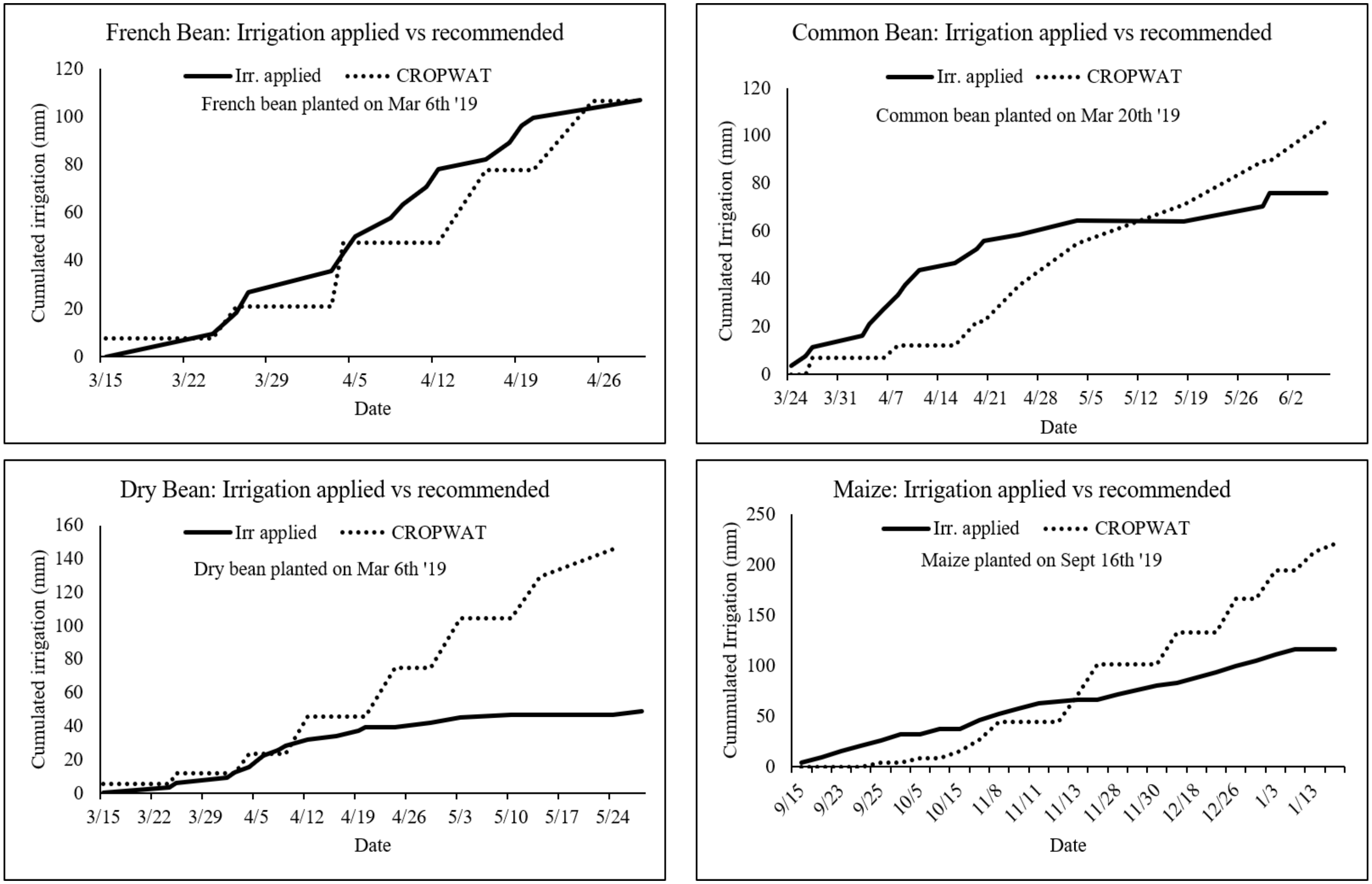


Figure 5. Comparison of cumulative net irrigation depth (mm) suggested by the CROPWAT model and real-time irrigation applied by farms in different crops growth stage and seasons

APPENDIX

A.1. Method

A.1.1 Calculation of Crop Water Requirement (CWR) and Irrigation Water Requirement (IWR)

The calculation of crop water requirement is usually guided by the estimation of Potential Evapotranspiration (ET_0). Although the Penman-Monteith method is recommended as the best ET_0 method for determining reference evapotranspiration, due to lack of weather data for the study site, ET_0 was estimated and compared for the given weather conditions, using two temperature-based methods:

A.1.1.1 Hargreaves-Samani method

Hargreaves-Samani method (1985) is an FAO recommended temperature-based empirical method, which has shown global validity with ET_0 calculation as given in FAO 56 Irrigation and Drainage Paper (Allen et al., 1998). Hargreaves-Samani has performed well in a sub-humid or semi-arid environment (Tabari, 2010); however, some literature reported it overestimates ET_0 (Djaman et al., 2015, Berti et al., 2014, Trajkovic, 2007). Daily estimates of ET_0 using the HS-ET_0 method is presented in Figure 3(b).

Hargreaves-Samani Equation:

$$ET_0 = 0.0023(T_{mean} + 17.8)(T_{max} - T_{min})^{0.5} R_a \qquad \text{Eq. 1}$$

where, R_a= Extraterrestrial Radiation ($MJm^{-2}hr^{-1}$), T_{mean}= Average temperature (^{o} C), T_{max}= Maximum Temperature (^{o} C), T_{min} = Minimum Temperature (^{o} C)

Based on each day of the year for different latitudes, R_a can be estimated from the solar constant, the solar declination as (Allen et al., 1998):

$$R_a = \frac{12(60)}{\pi} G_{sc} d_r [(\omega_s) \sin(\varphi) \sin(\delta) + \cos(\varphi) \cos(\delta) (\sin(\omega_s))] \qquad \text{Eq. 2}$$

where, G_{sc} = Solar constant (0.0820 MJ m^{-2} min^{-1}), d_r = inverse relative distance Earth-Sun, δ = Solar declination (rad), φ = latitude (rad), ω_1 = solar time angle at the beginning of the period (rad), ω_2 = solar time angle at the end of period (rad)

Other factors, such as d_r, δ, ω_s, were calculated based on the day of the year.

$$d_r = 1 + 0.33\cos\left(\frac{2\pi}{365} J\right) \qquad \text{Eq. 3}$$

$$\delta = 0.409\sin\left(\frac{2\pi}{365} J - 1.39\right) \qquad \text{Eq. 4}$$

where, J = calendar day of the year

$$\omega_s = \arccos\left(-\tan(\varphi)\tan(\delta)\right) \qquad \text{Eq. 5}$$

A.1.1.2 CROPWAT modified Penman-Monteith method

CROPWAT 8.0 simulation software was used to calculate crop water requirements for major crop types under the irrigation scheme. Specifically, CROPWAT modified Penman-Monteith method (Eq. 6) was used to calculate the reference crop evapotranspiration based on Minimum and Maximum temperature data (Table 2).

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\left(\frac{900}{T+273}\right) U_2 (e_a - e_d)}{\Delta + \gamma(1 + 0.34U_2)} \qquad \text{Eq. 6}$$

Where, ET_0 = reference evapotranspiration [mm day^{-1}], R_n = net radiation at the crop surface (MJm^{-2} day^{-1}), G = soil heat flux density (MJm^{-2} day^{-1}), T = mean daily air temperature at 2m height (°C), U_2 = wind speed at 2m height (m s^{-1}), e_a = saturation vapor pressure (kPa), e_d = actual vapor pressure (kPa), (e_a-e_d) = saturation vapor pressure deficit (kPa), Δ= slope vapor-pressure curve (kPa°C^{-1}), γ= psychrometric constant (kPa °C^{-1}), 0.408 converts the net radiation expressed in MJm^{-2}day^{-1} into equivalent evaporation expressed in mm day^{-1}

The model estimates the rest of the parameters, such as humidity (%), wind speed (km day^{-1}), sunshine hours, and Solar Radiation (MJ m^{-2}day^{-1}). CROPWAT uses temperature, latitude, and longitude of a specific location and adjusts weather parameters for the local average value of the atmospheric pressure to estimate other parameters (Clarke et al., 2001; Marica, 2005). Although monthly climatic values are input to the model, ET_0 outputs for each day are calculated (as mm day^{-1}). The monthly values are converted into daily values using the four distribution models within the CROPWAT model, and the default is a 2nd order polynomial curve fitting (Moseki, 2019; Marica, 2005; Clarke et al., 2001).

Humidity calculation is guided by the estimates of actual vapor pressure (e_a). An estimate of e_a is obtained by the assumption that dewpoint temperature (T_{dew}) is approximately equal to the daily minimum temperature (T_{min}) in a humid climate. Solar Radiation (R_s) was estimated from the calculation of R_a (Eq. 2) using the formula:

$$R_s = k_{Rs}(T_{max} - T_{min})^{0.5} * R_a \qquad \text{Eq. 7}$$

Where,

k_{Rs} = adjustment coefficient (0.16 .. 0.19) (°C$^{-0.5}$). For 'interior' locations, where landmass dominates, and air masses are not strongly influenced by a large water body, $k_{Rs} \cong 0.16$. For 'coastal' locations, situated on or adjacent to the coast of a large landmass and where air masses are influenced by a nearby water body, $k_{Rs} \cong 0.19$.

A.1.1.3 Crop evapotranspiration

Crop evapotranspiration (ET_c**)** is defined as the water flux to the atmosphere through soil evaporation and plant transpiration. ET_c was calculated using the well-established single crop coefficient approach (K_c) in FAO 56 (Allen et al., 1998). The model adjusts the ET_c for any soil water stress (Eq. 8).

$$ET_c = K_c * ET_0 * K_s \qquad \text{Eq. 8}$$

Where,

ET_c = Crop evapotranspiration, K_c = Crop coefficient, and K_s = soil water stress coefficient

K_c is a crop factor predominantly affected by crop characteristics and plant growth stages. K_c values of crops for the initial stage, development stage, mid-season, and harvest period were taken from FAO 56 paper (Allen et al., 1998). CROPWAT interpolates K_c and K_s values based on the development stage and water applied for different crops. Where field conditions differ from the standard conditions, correction factors are required to adjust ET_c. K_s values may vary between 0 (max water stress) and 1 (no water stress) as a function of simulated soil water depletion in the root zone on each day. K_s values are used in the equation to adjust the ET_c to current management practices and given environmental conditions. The Critical depletion fraction (p) in Eq. 9 represents the critical soil moisture level where first drought stress occurs affecting crop evapotranspiration and crop production and is a function of the evapotranspiration power of the atmosphere. *p*-values are expressed as a fraction of Total Available Water (TAW) and normally vary between 0.4 and 0.6, with lower values taken for sensitive crops with limited rooting systems under high evaporative conditions, and higher values for deep and densely rooting crops and low evaporation rates. The adjustment reflects the effect on crop evapotranspiration of the environmental and management conditions in the field.

$$K_s = \frac{TAW - D_r}{(1-p)TAW} \qquad \text{Eq. 9}$$

Where, *TAW* = Total Available Water, D_r = Depletion in the crop root zone, *p* = critical depletion fraction

A.1.2 Cobb-Douglas model for Econometric estimation

The Cobb-Douglas production function is expressed as a linear relationship using the following expression:

$$Y = \prod_{i=1}^{n} x_i^{a_i} \qquad \text{Eq. 11}$$

By taking natural logs on both sides, we get

$$\ln Y_i = \sum \alpha_i \ln(x_i) \qquad \text{Eq. 12}$$

Assuming yield as a function of input energies, for an investigation of the impact of each input energy on crop yield, the above equation can be expanded in the following form:

$$\ln Y_i = \alpha_1 ln x_1 + \alpha_2 ln x_2 \ldots . \alpha_n ln x_n \qquad \text{Eq. 13}$$

Where,

Y_i = Crop yield (kgha^{-1}) of the ith farm, α_n = coefficients of inputs estimated by the model and, $x_1, x_2, \ldots x_n$= input energies (MJha^{-1}) from different sources.

A.1.3 Calculation of Energy use equivalent (EUE)

The energy equivalent for a kg of NPK fertilizer and CAN fertilizer was derived from the ratio of elements (N, P, K, and Ca) in the fertilizers. In Kagitumba, 15:15:15 NPK fertilizer is commonly used. Energy equivalents for N, P, K, and Ca were used from the literature cited in Table 1. The following method/equations were used to calculate the energy equivalent of NPK and CAN. For example, Eq. 14 shows the calculation of EUE for NPK

$$EUE\ of\ NPK\ = \frac{(EUE_{N}*\ Q_N + EUE_{P205}*\ Q_{P205} + EUE_{K2O}*\ Q_{K2O})}{Weight\ of\ the\ fertilizer\ bag} \qquad \text{Eq. 14}$$

NPK calculation			
	%	Quantity of elements (Q)	EUE
N	15%	(15/100)*50 = 7.5	78.1* 15 = 585.75
P_2O_5	15%	(15/100)*50 = 7.5	17.4*15 = 130.5
K_2O	15%	(15/100)*50 = 7.5	13.7*15 =102.75
			16.38

CAN Calculation			
	%	Q	EUE
Ca	8%	8/100*50 = 4	9.9*4 = 39.6
N	27%	27/100*50 = 13.5	78.1* 13.5 = 1054.35
			21.879

A.1.4 Catch Can test for system performance evaluation

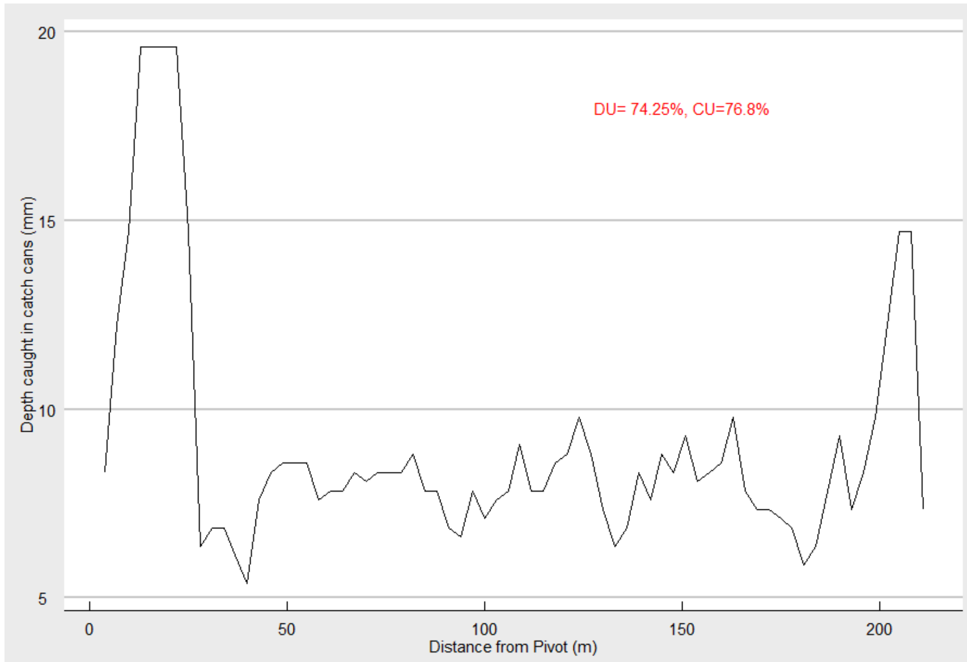
We performed a catch-can test for some pivots in section A where there was no crop planted and had the scope of conducting the analysis. The cans were set out in a grid with a spacing of 3 meters (*ca.*10 feet) between adjacent cans. We recorded the depth of water in each can in a spreadsheet. Figure A.1.1 shows the distribution of depth caught in the catch cans with respect to the particular distance from the pivot. Eq 15 and Eq 16 were used to calculate distribution uniformity (DU, %) and coefficient of uniformity (CU, %). For pivot A4, the calculated DU was 74.3%, and CU was 76.8%, and for pivot A12, calculated DU was 71.3%, and CU was 75.5%. The Natural Resources Conservation Service (NRCS) generally follows the following range of CU ratings: > 90%: Excellent, 85 - 90%: Good, 80 - 85%: Fair, and < 80%: Poor (Harrison and Perry, 2007).

$$DU = \frac{d_{LQ}}{d_z} * 100 \qquad \text{Eq. 15}$$

$$CU = \left[1 - \sum_{i=1}^{n} \frac{|d_z - d_i|}{n d_z}\right] * 100 \qquad \text{Eq. 16}$$

Where,

d_{LQ}= average depth caught in the low quarter, d_z= average depth caught in catch cans, d_i= depth caught in ith can, n= number of the catch can set up in the grid.



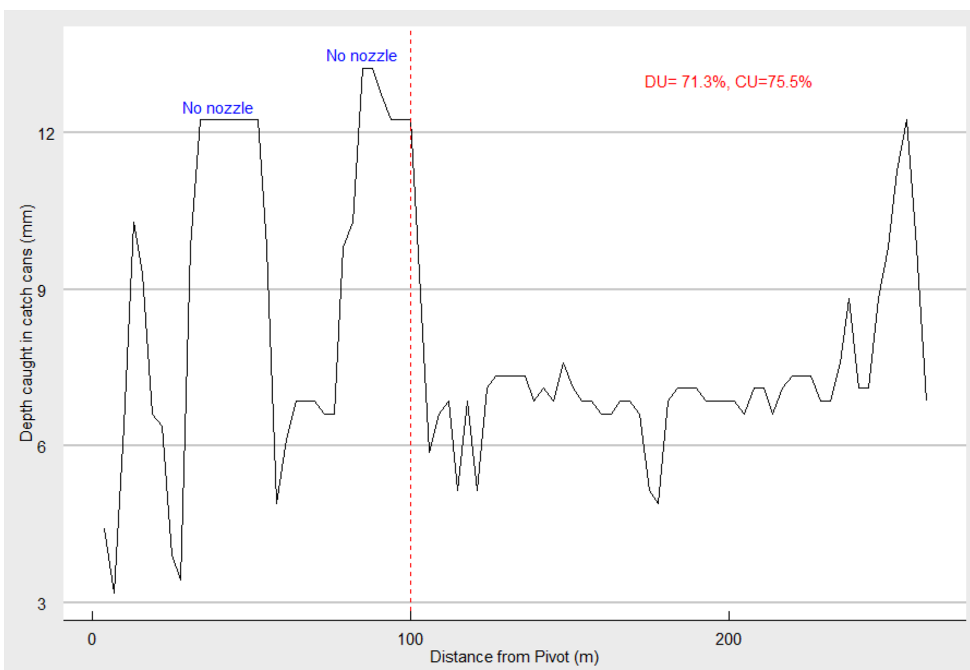


Figure A.1.1 Application distribution plot of catch can test in pivots #A4 (top) and #A12 (below) under Kagitumba Irrigation Scheme

A.2. Datasets related to CROPWAT 8.0

Table A.2.1. Estimated reference crop ET using CROPWAT 8.0 modified Penman-Monteith method

Month	Min Temp	Max Temp	Humidity	Wind	Sun	Rad	ET_o
	(°C)	(°C)	(%)	km/day	hrs	MJ/m²/day	mm/day
January	15.8	28.7	73	173	8.7	22.4	**4.68**
February	14.1	29.7	69	173	5.4	17.9	**4.31**
March	15.5	27.8	74	173	8.3	22.6	**4.62**
April	15.4	29.6	71	173	9.4	23.5	**4.94**
May	15.7	28.1	74	173	8.3	20.5	**4.28**
June	16.1	27.9	74	173	8	19.3	**4.04**
July	14	28.4	71	173	9.4	21.6	**4.44**
August	14.3	28.7	71	173	9.4	22.8	**4.69**
September	15.5	29	72	173	9	23.2	**4.86**
October	15.7	27	75	173	7.8	21.5	**4.38**
November	16.2	27.2	76	173	7.6	20.7	**4.25**
December	16.1	27.8	75	173	8	21	**4.34**
Average	15.4	28.3	73	173	8.3	21.4	**4.49**

Table A.2.2. Effective Rainfall calculation extracted from CROPWAT 8.0

	Rain (mm)	**Eff rain (mm)**
January	4.0	4
February	86.3	74
March	99.3	84
April	67.6	60
May	80.8	70
June	64.9	58
July	1.4	2
August	54.4	50
September	66.0	59
October	209.2	139
November	82	72
December	48.7	45
Total	864.6	716

Table A.2.3. Physiological and phenological crop inputs in CROPWAT

Crop parameters	French Bean	Common bean	Dry Bean	Maize
Duration of initial stage	10	20	20	20
Duration of development stage	20	30	30	35
Duration of mid-season	20	25	20	40
Duration of late season	10	10	20	40
Crop coefficient (Kc), initial stage	0.5	0.5	0.4	0.3
Crop coefficient (Kc), mid-season	1.05	1.05	1.2	1.2
Crop coefficient (Kc), late season	0.9	0.9	0.35	0.35
Rooting depth, initial stage (m)	0.2	0.3	0.3	0.3
Rooting depth, mid-season (m)	0.5	0.7	0.9	1
Crop height, mid-season (m)	0.28	0.4	0.4	2
Critical depletion fraction, initial stage	0.4	0.45	0.45	0.55
Critical depletion fraction, mid-season stage	0.4	0.45	0.45	0.55
Critical depletion fraction, late season	0.6	0.6	0.6	0.8
Yield response factor, initial stage	0.2	0.2	0.2	0.4
Yield response factor, mid-season	1.1	1.1	0.6	0.4
Yield response factor, development stage	0.75	0.75	1	1.3
Yield response factor, late season	0.4	0.4	0.2	0.5

A.3. Tables and Figures

Table A.3.1 Regression results and summary explaining the relationship between crop yield and water components in (a) Maize, (b) French beans, (c) Dry beans, (d) Common beans

(a)

Coefficients

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-129.729	62.87755	-2.063	0.0435*
ET	18.4735	7.53203	2.453	0.0172*
Net Irrigation	0.08691	0.05637	1.542	0.1285
Effective rainfall	3.54053	4.15264	0.853	0.3973
ΔSW	0.6709	0.25582	2.623	0.0111*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
Residual standard error: 0.1444 on 59 degrees of freedom
Multiple R-squared: 0.1496, Adjusted R-squared: 0.09199
F-statistic: 2.596** on 4 and 59 DF, p-value: 0.04537, N= 64

(b)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	7.4177	8.5124	0.871	0.3944
ET	2.5609	1.837	1.394	0.1794
Net Irrigation	0.9575	0.4108	2.331	0.0309*
Effective rainfall	-3.3844	2.5844	-1.31	0.206
ΔSW	-0.1518	0.1381	-1.099	0.2855

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
Residual standard error: 0.1705 on 19 degrees of freedom
Multiple R-squared: 0.6168, Adjusted R-squared: 0.5362
F-statistic: 7.647*** on 4 and 19 DF, p-value: 0.000756, N= 24

(c)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-5.79886	26.05347	-0.223	0.8245
ET	0.34379	13.65374	0.025	0.98
Net Irrigation	-0.14594	0.06523	-2.237	0.0286*
Effective rainfall	2.22641	10.06184	0.221	0.8255
ΔSW	-0.11886	0.22273	-0.534	0.5953

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
Residual standard error: 0.1157 on 68 degrees of freedom
Multiple R-squared: 0.08538, Adjusted R-squared: 0.03157
F-statistic: 1.587 on 4 and 68 DF, p-value: 0.1878, N= 68

(d)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)

(Intercept)	-11.00411	55.89658	-0.197	0.845
ET	-5.29776	24.57326	-0.216	0.831
Net Irrigation	0.16558	0.10355	1.599	0.119
Effective rainfall	9.11411	17.25326	0.528	0.601
ΔSW	-0.02523	0.18128	-0.139	0.89

Residual standard error: 0.2484 on 35 degrees of freedom
Multiple R-squared: 0.08947, Adjusted R-squared: -0.01459
F-statistic: 0.8598 on 4 and 35 DF, p-value: 0.4976, N= 40

Table A.3.2 ANOVA test results showing analysis of water components impacting crop yield

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
French Bean					
ET_0	1	3687629	3687629	2.7822	0.1017153.
I_a	1	25501355	25501355	19.2399	0.0003174***
P_e	1	7253472	7253472	5.4725	0.0303932*
ΔSW	1	2099934	2099934	1.5843	0.2233855
Residuals	19	25183433	1325444		
Common Bean					
ET_0	1	22742	22742	0.3652	0.5495
I_a	1	102172	102172	1.6407	0.2087
P_e	1	4231	4231	0.0679	0.7959
ΔSW	1	9110	9110	0.1463	0.7044
Residuals	35	2179553	62273		
Dry Bean					
ET_0	1	8886	8886	0.6309	0.42979
I_a	1	65538	65538	4.6529	0.03454*
P_e	1	230	230	0.0163	0.89876
ΔSW	1	1601	1601	0.1136	0.73708
Residuals	68	957801	14085		
Maize					
ET_0	1	111233	111233	0.1844	0.66918
I_a	1	1257361	1257361	2.0845	0.10409.
P_e	1	624840	624840	1.0359	0.31293
ΔSW	1	2724044	2724044	4.5161	0.03778*
Residuals	59	35587916	603185		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Table A.3.3 Energy use and total embodied energy in different crops in Season B

Input	Quantity per ha	Total energy use (MJ/ha)	Percentage (%)
French Beans			
Seed	42.7 kg	139	0.6%
Labor	3032 hrs	5943	25.7%
Machinery	3 hrs	194	0.8%
Fertilizers			50%
- NPK	203 kg	3329	
- DAP	196 kg	3403	
- CAN	220 kg	4821	
Agro-chemicals			7.3%
- Insecticide	0.87 kg	395	
- Fungicide	11 kg	1296	
Irrigation water	341 m^3	215	0.9%
Electricity	282 kWh	3384	14.6%
		23119	
Yield	7092 kg	101416	
Common Beans			
Seed	59 kg	832	4.2%
Labor	1134 hrs	2223	49.3%
Machinery			0
Fertilizers			0
Agro-chemicals			0
Irrigation water	727 m^3	458	10.2%
Electricity	144 kWh	1728	36.3%
		5241	
Yield	944 kg	13310	
Dry Beans			
Seed	81 kg	1628	25.4%
Labor	894 hrs	1752	27.5%
Machinery			0
Fertilizers			0
Agro-chemicals			0
Irrigation water	462 m^3	291	4.6%
Electricity	254 kWh	3048	42.6%
		6719	
Yield	1033 kg	20763	

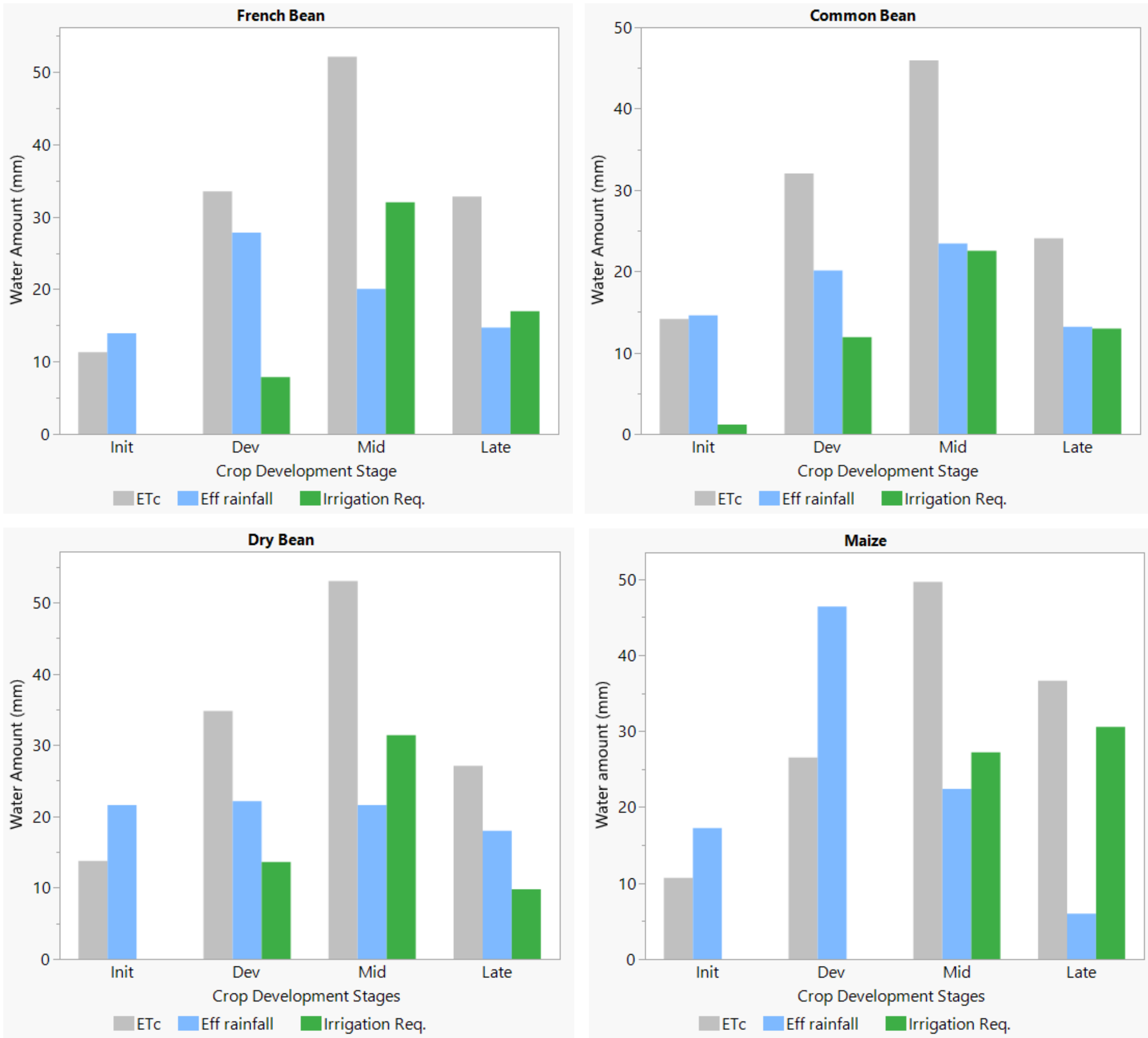


Figure A.3.1. Crop evapotranspiration, effective rainfall, and irrigation requirement at different developmental stages of French bean, common bean, dry bean and (d) maize. The plots represent critical growth stages for water requirements and rainfall in the crops (Init= initial phase, Dev= development phase, Mid= Mid phase, Late- late phase).

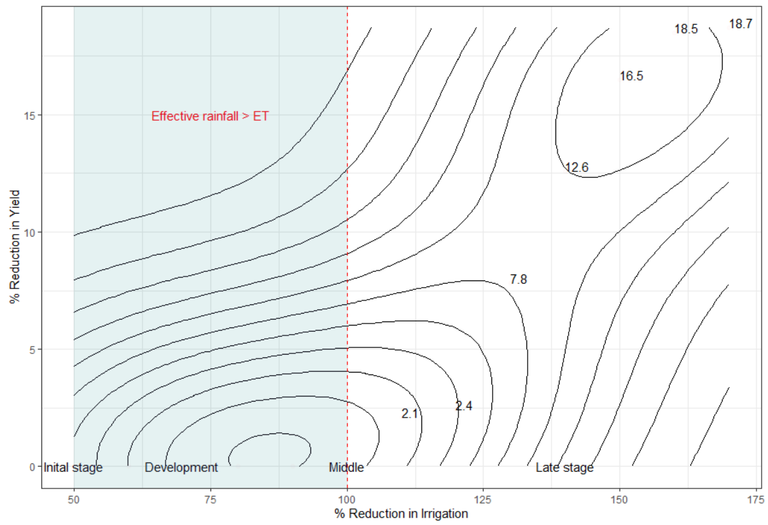


Figure A.3.2. Yield reduction in maize by consequent 10% decrease in modeled irrigation rate in each crop developmental stage

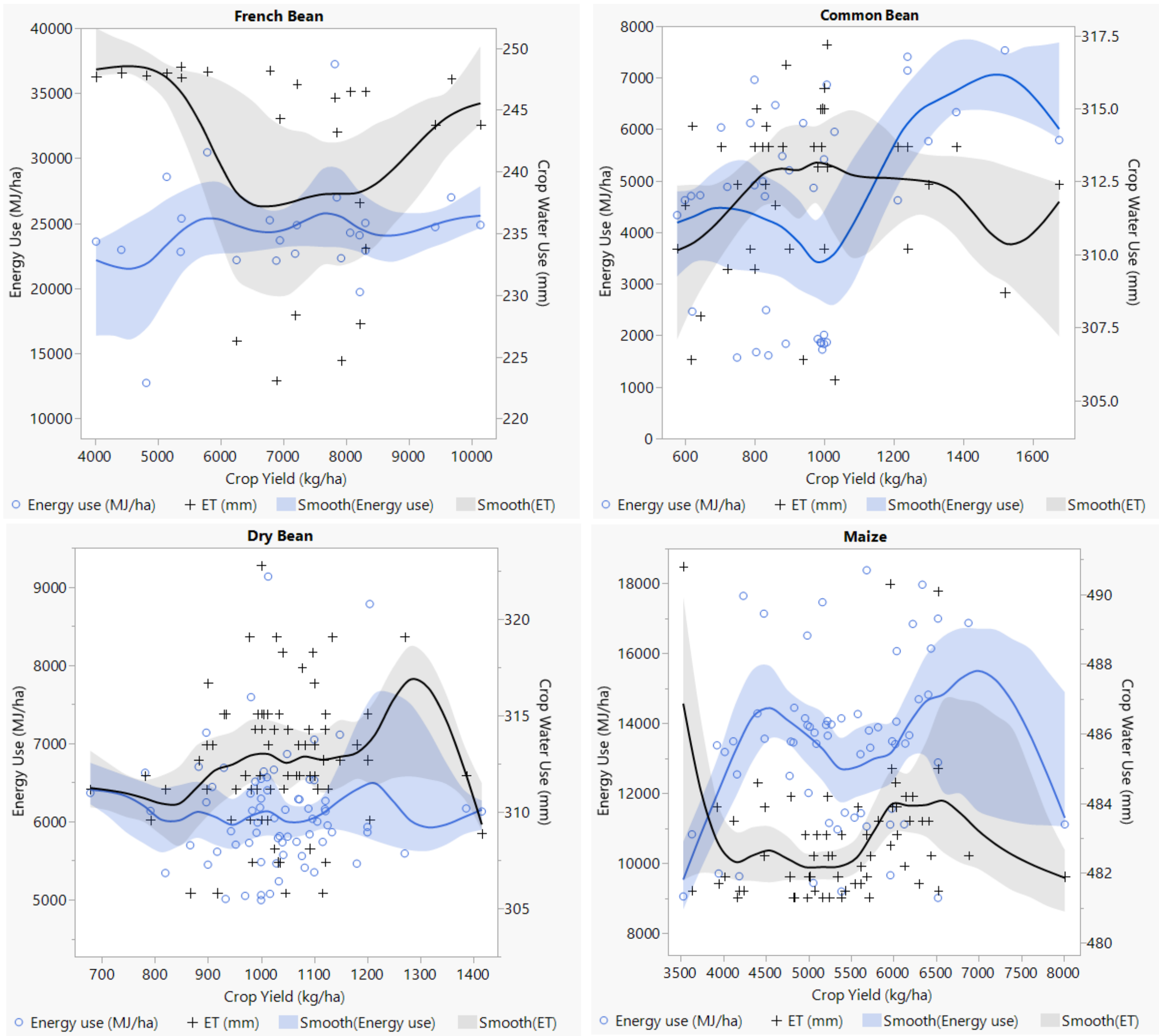


Figure A.3.3. Water-energy-food curve showing the total amount of energy use (MJ ha^{-1}) and crop water use (mm) in Beans and Maize. Smoothness in the plot represents 95% confidence interval of robust fitted data.